Examining the efficacy of Guided Imagery relaxation technique in reducing stress, modulating brain wave activity, and enhancing attention control

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27 May, 2024

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Abstract

This thesis presents a comprehensive investigation into relaxation techniques, focusing on the impact of Guided Imagery (GI) on cognitive and emotional functions, and exploring the potential applications of machine learning classifiers in therapy support and brain-computer interfaces (BCI). The study, which included 60 right-handed male participants aged 17-24, illuminates GI's capacity to enhance mental well-being and focus attention. Received findings demonstrate the effectiveness of GI in enhancing cognitive performance and emotional balance by modulating alpha power and attention regulation. Moreover, the study explores the complex connections between variables, laying the groundwork for tailor-made interventions that address the diverse aspects of cognitive and emotional functioning.

The content has been reorganized to include a detailed review of mindfulness practices and their classification, an exploration of guided imagery, and a thorough examination of the effects of relaxation techniques on cognitive functions and alpha oscillations. The introduction section now provides a deeper dive into these topics, establishing a solid foundation for the subsequent research. These modifications and additions ensure that the thesis not only addresses the initial research questions more comprehensively but also aligns with the reviewers' feedback, enhancing the depth of the study. While acknowledging limitations such as the relatively modest sample size and the exclusive focus on healthy male subjects, this study presents the potential application of GI as an effective support tool for well-being and attention control.

Streszczenie

Niniejsza praca prezentuje kompleksowe badanie dotyczące wpływu techniki relaksacyjnej - wyobraźni prowadzonej (GI) na funkcje poznawcze i emocjonalne. Dodatkowym aspektem badania była eksploracja potencjalnych zastosowań klasyfikatorów uczenia maszynowego (GLM) w wsparciu terapeutycznym i tworzeniu na tej podstawie interfejsów mózg-komputer, które byłyby indywidualnie dopasowane do potrzeb użytkownika. Badanie przeprowadzone na 60 praworęcznych mężczyznach w wieku od 17 do 24 lat weryfikuje możliwości zastosowania GI w celu poprawy dobrostanu psychicznego, zwłaszcza w indukowaniu stanu relaksu. Otrzymane wyniki wykazują skuteczność GI w poprawie uwagi i równowagi emocjonalnej poprzez modulację mocy alfa i redukcję stresu. Ponadto badanie poszukuje zależności między zmiennymi, w celu lepszego zrozumiania wpływ GI na funkcjonowanie poznawcze i emocjonalne uczestników badania.

Zawartość pracy została zreorganizowana i rozbudowana w taki sposób, aby zawrzeć szczegółową analizę praktyk uważności i sposobów ich klasyfikacji. Zaprezentowany w pracy przegląd wpływu technik relaksacyjnych na funkcje poznawcze i oscylacje alfa pozwala na lepszą argumentację postawionych w pracy hipotez. Wprowadzone modyfikacje zapewniają, że praca bardziej dokładnie opisuje schematy działania technik relaksacyjnych, ale także odpowiada na sugestie recenzentów, wzbogacając wnioski z badania. Mimo wskazanych w pracy ograniczeń, takich jak stosunkowo niewielki rozmiar próby i wyłączne skupienie się na zdrowych mężczyznach, badanie prezentuje potencjał GI jako skutecznego narzędzia wpływającego na zwiększenie stanu relaksu oraz poprawę uwagi u badanych osób.

Chapter 1

Introduction

1.1 Introduction

The study of relaxation techniques has become increasingly important in contemporary scientific research, given their potential to improve well-being and cognitive functioning. This research focuses on exploring Guided Imagery (GI), a relaxation method, to understand its effectiveness in promoting relaxation and enhancing attentional control. The aim was to verify if Guided Imagery has the potential to induce relaxation, and second, what is their impact on attentional mechanisms. Our theoretical framework suggests that changes in attentional control may be linked to alterations in alpha wave activity, which we intend to investigate through electroencephalogram (EEG) readings during Guided Imagery sessions. Our deliberations are grounded in a comprehensive review of existing literature on relaxation techniques, aiming to elucidate the current understanding of their effects on cognitive functions. The exploration of relaxation techniques dates back centuries, with contemplative traditions such as Buddhism and Yoga emphasizing the importance of mental focus, clarity, and emotional regulation. Within these traditions, practices such as meditation and visualization have been employed as tools for achieving inner peace, heightened awareness, and spiritual growth. The modern scientific interest in relaxation techniques emerged in the mid-20th century, with researchers investigating their potential therapeutic benefits for stress reduction, anxiety management, and overall well-being. Numerous studies presented in the thesis investigated the effects of relaxation techniques on various aspects of cognitive functioning, such as attention, memory, and executive function. Research suggests that relaxation practices, particularly mindfulness-based interventions (MBI), can lead to improvements in attentional control, cognitive performance, and emotional regulation. Furthermore, reviewed studies examining the neural correlates of relaxation techniques have identified changes in brainwave activity, particularly in alpha and theta oscillations, following mindfulness practices. Alpha oscillations, which are associated with relaxed wakefulness and decreased mental activity, have been shown to increase during meditation and Guided Imagery sessions, indicating a state of relaxation and heightened awareness. In conclusion, the relaxation techniques, particularly Guided Imagery (GI), show promise as effective tools for promoting relaxation, enhancing attentional control, and improving overall well-being. This thesis aims to present these findings through a combination of theoretical frameworks, empirical research, and practical applications. Relaxation practices offer valuable insights into the complex interplay between the mind, body, and brain. While our understanding of relaxation techniques, including GI, continues to evolve, further research is needed to explore their precise mechanisms of action, optimal implementation strategies, and long-term effects on cognitive and emotional health.

1.2 Exploration of relaxation techniques

Relaxation techniques have long been studied for their effectiveness in reducing stress and promoting well-being (Jha et al., 2007; Scotland-Coogan & Davis, 2016; Sung, Roussanov, Nagubandi, & Golden, 2000). In the wake of the COVID-19 pandemic, war across the border, the need for stress reduction strategies has become even more critical, as individuals worldwide face not only physical health challenges but also social, psychological, and economic consequences (Mamun, 2021; Mertens, Gerritsen, Duijndam, Salemink, & Engelhard, 2020). Among the various relaxation methods explored, Guided Imagery has emerged as a valuable approach that has been extensively investigated in the fields of healthcare, sports psychology, and stress management (Mellenthin, 2021; Shafer & Greenfield, 2000). The field of contemplative science has witnessed a rapid surge in the exploration of how mindfulness impacts cognitive functioning. This inquiry is deeply rooted in the historical emphasis within contemplative traditions on honing concentration and perceptual clarity (Bishop et al., 2004; Grabovac, Lau, & Willett, 2011; Hölzel et al., 2011; Lin, Tang, & Braver, 2022). Scientific investigations into mindfulness have been intricately linked to cognition, with attention emerging as a central focus in theoretical models (Grabovac et al., 2011; Lutz et al., 2008; Lutz, Jha, Dunne, & Saron, 2015; Shapiro, Carlson, Astin, & Freedman, 2006; Lin et al., 2022; Vago & Silbersweig, 2012). Early research efforts predominantly concentrated on exploring the intersection of mindfulness and attentional abilities (Cahn & Polich, 2006; Teasdale, Segal, & Williams, 1995; Valentine & Sweet, 1999). However, as the field evolved, interest expanded to encompass a broader array of cognitive functions such as creativity and problem-solving, aiming to attain a more nuanced understanding of the neurocognitive underpinnings of mindfulness and its psychological benefits (Berkovich-Ohana, Glicksohn, Ben-Soussan, & Goldstein, 2017; Colzato, Szapora, Lippelt, & Hommel, 2017). Over the last two decades, research efforts have primarily focused on two overarching goals: firstly, to elucidate the relationship between mindfulness and cognitive functions, including identifying shared neurocognitive processes and their respective limitations, and secondly, to assess the efficacy of various forms of mindfulness training in modulating or enhancing cognitive abilities. Despite the substantial growth in empirical literature, achieving these aims has proven challenging due to methodological inconsistencies and varied findings across studies (Cahn & Polich, 2006; Teasdale et al., 1995; Valentine & Sweet, 1999).

1.3 A Review of Mindfulness Practice and Intervention Classifications

Mindfulness is an umbrella term that can refer to a state of mind, a charactero-logical trait, a form of contemplative practice, and a type of clinical intervention (Lin et al., 2022). For instance, focused attention (FA), open monitoring (OM), and loving-kindness (LK) meditation also known as compassion meditation are distinct meditative practices, yet they are frequently grouped under the overarching label "mindfulness meditation" (Lin et al., 2022; Fox et al., 2016; Manna et al., 2010). In addition, there is technical diversity among mindfulness practices, including variations in the duration and intensity of meditation training, which can vary dramatically across studies. There does not appear to be a common "standard" training interval, as seen with Mindfulness-Based Interventions (MBIs) (e.g., 8 weeks). (Lin et al., 2022). The duration of meditation studies ranged from as short as 1 or 2 weeks to longer periods of 3 to 10 weeks. Interestingly, in the Sedlmeier's meta-analysis (Sedlmeier, Loße, & Quasten, 2018) it was found that for very short training periods of 1 or 2 weeks, the effects of meditation seemed to be stronger compared to medium durations of 3 or 4 weeks. From the literature review it is known that a single brief induction may be insufficient to alter behavioral performance but can nonetheless affect neural processing. This suggests that sustained training may be necessary before mindfulness-induced plasticity translates to behavioral change (Bing-Canar, Pizzuto, & Compton, 2016; Larson, Steffen, & Primosch, 2013; Lin et al., 2022). In mindfulness training studies, longitudinal repeated assessments (i.e. pre- vs. post-intervention) are typically conducted to evaluate the impact of Mindfulness-Based Interventions (MBIs). Despite this straightforward approach, there is significant ambiguity in defining what constitutes an MBI (Cullen, 2011). Since the introduction of Jon Kabat-Zinn's influential Mindfulness-Based Stress Reduction (MBSR), there has been a proliferation of interventions incorporating mindfulness (Kabat-Zinn, 2003). However, variations in teaching methods, training techniques, and practical application of mindfulness make it difficult to establish a precise standard for MBIs. Sedlmeier's meta-analysis (Sedlmeier et al., 2018) examining the psychological impacts of meditation among healthy practitioners reveals that Insight meditation, also known as Vipassana meditation, stands out with the most favorable outcomes across various research dimensions. Insight meditation, rooted in Buddhist tradition, entails a methodical and disciplined approach to observing the present moment, encompassing thoughts, emotions, and bodily sensations with an non-reactive and non-judgmental attitude. Insight meditation can be categorized as a form of open monitoring (OM) meditation. The findings highlight the notable advantages of insight meditation, indicating consistently larger effects compared to other meditation modalities, except for compassion meditation. Insight meditation demonstrates substantial and uniform impacts, particularly in domains of interpersonal relationships, cognitive abilities, and self-perception. Furthermore, the practice exhibits positive influences on emotional intelligence, general self-efficacy, stress management, and emotional regulation. Moreover, insight meditation correlates with enhancements in cognitive functions, including both convergent and divergent thinking, as well as heightened creativity and mood regulation. As researchers continue to explore the impact of mindfulness meditation on cognitive function, there is growing evidence to support its role in promoting a state of calm and improving overall cognitive performance. From reductions in symptoms of anxiety and depression to alterations in brain wave activity indicative of enhanced attention and focus, the findings underscore the multi-faceted benefits of integrating mindfulness meditation into wellness routines. Mindfulness encompasses diverse practices that vary based on type (e.g., focused attention vs. open monitoring) and modality (e.g., walking vs. sitting), yet it shares certain features related to mental visualization and sensory involvement with Guided Imagery (GI). Eberth meta-analysis (Eberth & Sedlmeier, 2012) of 39 controlled studies examining the impact of mindfulness meditation on psychological factors reveals distinct patterns. Specifically, Mindfulness-Based Stress Reduction (MBSR) programs demonstrate pronounced effects on psychological well-being, stress reduction, mitigation of negative emotions, and alleviation of anxiety. Conversely, investigations focusing solely on mindfulness meditation without the structured MBSR framework, show the greatest influence on variables related to mindfulness itself, such as self-reported mindfulness, attentional capacities, and anxiety levels. Furthermore, the analysis highlights that MBSR primarily enhances psychological well-being, whereas "pure mindfulness meditation" predominantly affects mindfulness-related constructs. Consequently, the efficacy of mindfulness meditation varies across psychological domains, with MBSR exhibiting greater efficacy in fostering psychological well-being and stress reduction, while "pure mindfulness meditation" shows greater efficacy in enhancing mindfulness-related variables. The analysis of "pure" meditation refers to meditation practices that are distinct from mindfulness-based interventions such as Mindfulness-Based Stress Reduction (MBSR). The program typically integrates mindfulness meditation, body scan exercises, and yoga practices (Khoury et al., 2013), with the protocol commonly spanning an 8-week duration (Grossman, Niemann, Schmidt, & Walach, 2004). Its aim is to enhance individuals' consciousness of the present moment while equipping them with better tools to manage life's adversities. The term "pure" meditation serves to demarcate traditional meditation methodologies, including Vipassana, Zen/Chan, Shamatha, Vipshyana, Zazen, and other modalities, from interventions integrating mindfulness meditation within a structured regimen. "Pure" meditation typically involves the direct application of meditation techniques devoid of supplementary elements such as psychoeducation, cognitive therapy, or specific instructional courses commonly featured in mindfulness-based interventions. This differentiation between "pure" meditation and mindfulness-based interventions (MBI) is significant in the context of the document's meta-analysis, as it facilitates the examination of the specific impacts of traditional meditation practices on psychological parameters within nonclinical populations. Therefore the impact of mindfulness meditation varies across different psychological variables, with MBSR showing stronger effects on psychological well-being and stress reduction, while pure mindfulness meditation has larger effects on variables associated with mindfulness. Dahl, Lutz and Davidson (Dahl, Lutz, & Davidson, 2015) proposed a classification of meditation into attentional, constructive, and deconstructive families based on their primary cognitive mechanisms and proposes a novel framework to understand how alterations in these processes might impact levels of well-being. The attentional family focuses on attention regulation and meta-awareness, which can lead to increased attentional stability and reduced response time variability. The constructive family emphasizes nurturing harmonious relations with others and cultivation of virtuous qualities, which may impact specific psychological factors and enhance dimensions of well-being. The deconstructive family targets states of experiential fusion, maladaptive self-schema, and cognitive reification through self-inquiry and insight practices. These practices aim to reverse states of experiential fusion through the cultivation of meta-awareness, which is considered important for mental health.

1.4 Exploring Guided Imagery

Whereas mindfulness prioritizes present-moment awareness and acceptance, GI leans towards directive and goal-oriented approaches. A notable distinction between Guided Imagery and mindfulness lies in their primary objectives and underlying mechanisms. GI often prioritizes the creation of vivid mental images to influence behavior and self-regulation by strengthening the association between thoughts and goal-oriented actions. It frequently targets specific outcomes, such as boosting motivation, enhancing performance, or alleviating stress. Conversely, mindfulness practice centers on cultivating present-moment awareness, accepting experiences without judgment, and creating cognitive distance from negative thoughts and beliefs. Its goal is to foster mindfulness characterized by heightened attention to thoughts, emotions, and bodily sensations (Mellenthin, 2021; Mitchell, Martin, Baldwin, & Levens, 2021). While both Guided Imagery and mindfulness can induce relaxation and reduce stress, Guided Imagery tends to be more prescriptive and outcome-oriented, often employing specific imagery and prompts to shape behavior or emotional states. Guided Imagery is a technique that harnesses the power of imagination to bring about changes in physical, emotional, or spiritual aspects of an individual (Fitzgerald & LANGEVIN, 2009). It is a common practice in psychotherapy where relaxation methods are combined with the creation of mental images that engage all five senses: sight, sound, touch, taste, and smell. The purpose of this technique is to intentionally create specific images that can alter physiological and emotional states using the client's imagination (La Roche, Batista, & D'Angelo, 2011). GI involves the use of mental imagery to evoke sensory experiences and has gained significant attention as one of the oldest healing resources. It has been defined as the internal experience of a perceptual event in the absence of actual external stimuli, encompassing both sensory and cognitive dimensions (Heinschel, 2002). Guided Imagery and meditation share similarities as they both involve relaxation techniques and the use of mental imagery to influence physiological and emotional states. Both practices can be used to calm the mind and body, reduce stress and anxiety, and promote a sense of well-being. In terms of the FA (focused attention) and OM (open monitoring) types of meditation, Guided Imagery can incorporate elements of both. During Guided Imagery, individuals may focus their attention on specific mental images or scenarios (FA), while also remaining open to the sensory experiences and emotions that arise during the visualization process (OM). Therefore, Guided Imagery can be seen as a combination of FA and OM meditation techniques, providing a structured framework for visualization while allowing for open awareness of internal experiences (Mellenthin, 2021). Guided Imagery is known to impact multiple physiological systems, such as respiratory, cardiovascular, metabolic, gastrointestinal, and immune systems, by modulating the activity of the hypothalamic-pituitary-adrenal axis and promoting a state of relaxation and well-being (De Paolis et al., 2019; Sabatinelli, Lang, Bradley, & Flaisch, 2006).

1.5 Executive Functions, Cognitive Functions, and Attention Control

Attention and executive function are vital cognitive abilities in today's complex and demanding world. Extensive scientific research has underscored their crucial roles in various aspects of cognitive processing and goal-directed behavior (Stevens & Bavelier, 2012). Attention allows us to selectively focus on relevant information while filtering out distractions, making it essential for concentration, information processing, and decision-making (Johnson & Proctor, 2004). Enhanced attention and executive function have consistently been associated with improved academic results, job performance, and decision-making abilities (Arrington, Kulesz, Francis, Fletcher, & Barnes, 2014; King & Haar, 2017; Petersen & Posner, 2012; Titz & Karbach, 2014). Consequently, the enhancement of these cognitive functions is crucial in our information-rich environment and can benefit individuals and society as a whole (Trautwein, Kanske, Böckler, & Singer, 2020). Executive functions refer to a set of higher-level cognitive skills and capacities that are involved in planning, organizing, problem-solving, decision-making, and controlling behavior. These functions are essential for goal-directed behavior and the capacity to adapt and respond flexibly to changing environmental demands (Diamond, 2013; Miyake et al., 2000). Controlled by the pre-frontal cortex of the brain, these functions play a crucial role in goal-directed behavior (Berkman, 2018). Cognitive functions, on the other hand, encompass a broad range of mental processes such as perception, memory, language, reasoning, and attention. These functions are essential for information processing and are closely linked to executive functions (Elliott, 2003). Attention control, as a component of cognitive functions, refers to the ability to selectively focus on relevant information while inhibiting irrelevant or distracting stimuli. It is essential for filtering out distractions and maintaining focused attention on a specific task or a goal (Eysenck, Derakshan, Santos, & Calvo, 2007; Mackie, Van Dam, & Fan, 2013). Several studies have explored the relationship between executive functions, cognitive functions, and attention control (Diamond, 2013; Miyake et al., 2000). These theories provide different perspectives on how these functions operate and interact with each other in the brain, contributing to our understanding of cognitive processes and behavior. Miyake (Miyake et al., 2000) proposed three interrelated subsystems of executive control: shifting, updating, and inhibition. The shifting aspect of executive control refers to the ability to quickly and accurately switch attention between different stimuli or tasks. The updating aspect involves the constant refreshing of information in the attentional area, such as holding and updating working memory during a busy shift or keeping track of orders and statuses in a restaurant setting. The inhibition aspect of executive control refers to the cognitive ability to refrain from updating or shifting attention to distracting stimuli. These subsystems of executive control work together to facilitate goal-directed behavior and adaptability. DDiamond describes executive functions as a set of cognitive processes responsible for goal-directed behavior and the ability to adapt and respond flexibly to changing environmental demands (Diamond, 2013). In our fast-paced, information-rich environments, the cultivation of executive functions is increasingly crucial for effective task performance and productivity. The ability to manage attention, switch between tasks, and exercise inhibitory control is fundamental to successful human functioning in today's complex and dynamic world (Miyake et al., 2000; Friedman, 2015). Research findings consistently indicate that anxiety impairs attentional control and cognitive performance, particularly under conditions of high cognitive demand. Since attention control plays a vital role in cognitive functions, it is often assessed using various tests. The Stroop test, Go/No-Go task, and Anti-Saccade task are commonly used in research because they specifically target and assess different aspects of attention. While all three tests are measures of executive function, they differ in their specific cognitive demands and the underlying processes they assess. The Stroop test measures attention control and the ability to inhibit automatic responses and maintain focus on the task at hand. The most common version of this test involves colored words printed in different ink colors (e.g., the word "red" printed in blue ink) and individuals are asked to name the ink color while ignoring the word's meaning. The interference caused by the conflicting information measures the individual's ability to focus attention and suppress automatic reading responses. Stroop tasks assess selective attention and inhibition of irrelevant information (Meule, 2017). The Go/No-Go task assesses inhibitory control and working memory (Meule, 2017). Participants are required to respond to certain stimuli (go trials) but withhold responses to others (no-go trials). This test measures the ability to inhibit prepotent responses and maintain focused attention. It has been proven that acute psychosocial stress may affect executive action control in a Go/No-Go task (Scholz et al., 2009). The Go/No-Go test has been used in studies examining attentional control across different age groups, clinical populations, and in relation to various cognitive functions (Pacheco-Unguetti, Acosta, Lupiáñez, Román, & Derakshan, 2012). The Anti-Saccade task evaluates the ability to inhibit reflexive eye movements and voluntarily shift attention (Miyake et al., 2000; Hellmuth et al., 2012). Participants are instructed to look away from a suddenly appearing visual stimulus. Successful performance on this task requires inhibiting the automatic saccadic eye movement towards the stimulus and voluntarily redirecting attention. Another widely used cognitive task paradigm that measures cognitive control and attentional processes is the flanker test. In this task, participants are presented with a central target stimulus, such as an arrow, and are required to respond to its direction while ignoring distracting stimuli, or "flankers", that are presented alongside the target. The flankers can either be congruent (i.e. pointing in the same direction as the target) or incongruent (i.e. pointing in the opposite direction). The main goal of the flanker test is to assess the participant's ability to inhibit attention to the distracting flankers and focus on the relevant target stimulus. The test is often used in research to investigate the impact of various interventions, such as mindfulness meditation training, on cognitive performance and control (Lin et al., 2022). The ANT, or Attention Network Test, is another cognitive task used to measure attentional control and executive function. It consists of a series of visual stimuli, including arrows pointing in different directions, and requires participants to respond to specific cues while inhibiting responses to distracting information. The test assesses three main attentional networks: alerting, orienting, and executive control. The alerting network is responsible for achieving and maintaining a state of high sensitivity to incoming stimuli; the orienting network is involved in the selection of information from sensory input; and the executive control network is responsible for resolving conflicts in information processing. The ANT is commonly used in research to investigate the effects of mindfulness-based interventions and other cognitive training programs on attentional performance (Lin et al., 2022). These attention control tests provide insights into an individual's cognitive processes and contribute to understanding the intricate relationship between executive functions, cognitive functions, and attention control as presented in Table 1.1. By assessing attentional abilities, these tests offer valuable information about an individual's capacity to manage and regulate their attention, which is essential for successful functioning in various cognitive and behavioral contexts.

Cognitive Task	**Key Feature**	**Common Use**
Stroop Task	Measures cognitive control and inhibitory control	Assessing attention, processing speed, and interference control
Anti-Saccade Task	Evaluates inhibitory control and voluntary eye movement	Studying cognitive flexibility, response inhibition, and executive functions
Flanker Task	Assesses selective attention, response inhibition, and cognitive control	Examining interference control, attentional focus, and the ability to filter out irrelevant information
Go/No-Go Task	Evaluates response inhibition, impulsivity, and cognitive flexibility	Investigating inhibitory control, response accuracy, and decision-making speed
Attention Network Test	Measures alertness, spatial orienting, and conflict resolution abilities	Studying different components of attention and their interactions in cognitive tasks

Table 1.1: Overview of attentional tests. Table compiled by Katarzyna Zemła based on (Bari & Robbins, 2013; MacLeod, 1991; Munoz & Everling, 2004; Posner & Petersen, 1990)

1.6 The Effects of Anxiety and Stress on Cognitive Function.

Anxiety's influence on cognitive function has been extensively explored across multiple studies and theoretical frameworks. One prominent framework is the processing efficiency theory, which suggests that anxiety disproportionately affects processing efficiency rather than performance effectiveness (Eysenck et al., 2007). This discrepancy arises from the diminished engagement of the goal-directed attentional system and heightened involvement of the stimulus-driven attentional system in anxious individuals. Consequently, individuals experiencing anxiety are more prone to distraction by both internal and external stimuli, impairing their inhibition and shifting functions. Moreover, as the demands of the central executive task escalate, the adverse impacts of anxiety on performance intensify. This escalation makes it increasingly challenging for anxious individuals to compensate for impaired efficiency through heightened effort and resource utilization. Eysenck delineates the differentiation between effectiveness and efficiency in task execution, noting that efficiency diminishes as additional resources are allocated to achieve a specific performance level.

Research has demonstrated that chronic stress induces dendritic atrophy in hippocampal neurons, suppresses neurogenesis, and leads to hippocampal volume reduction (Lupien, McEwen, Gunnar, & Heim, 2009). These structural changes correlate with deficits in spatial learning and memory, which exhibit potential for reversal following a period of stress alleviation (Lupien et al., 2009). In humans, chronic stress is associated with diminished hippocampal volume and cognitive impairments, particularly among individuals with low self-esteem. The effects of chronic stress on the brain and cognitive functions are intricate and contingent upon factors such as the timing and duration of exposure, as well as individual susceptibility. Stress can exert multifaceted effects on cognitive function, with the specific outcomes contingent upon various factors related to both stress and the cognitive task at hand. The intensity or magnitude, origin (task-induced or external), and duration (acute or chronic) of stress all contribute to shaping its impact on cognition. Moreover, the nature of the cognitive operation (e.g., implicit or explicit memory, long-term or working memory, goal-directed or habit learning) and the distinct phases of information processing (e.g., learning, consolidation, and retrieval) are crucial determinants of how stress influences cognition (Sandi, 2013).

Chronic stress represents a considerable threat to human health and cognitive function, manifesting in various challenging facets of life. It can precipitate the onset of stress-related disorders like burnout, depression, and PTSD, while also exacerbating pre-existing vulnerabilities (Marin et al., 2011). Key factors such as gender, early life experiences, and genetic predispositions substantially influence individuals' perception and response to stress, thereby impacting stress reactivity, cognition, and susceptibility to developing psychopathologies. Furthermore, prolonged stress can influence individuals' cognitive evaluations and perceptions of situations, perpetuating a cycle that proves difficult to escape from (Marin et al., 2011).

In conclusion, exploring techniques that release stress and induce relaxation can offer valuable insights into the enhancement of cognitive abilities.

1.7 Exploring the Effects of Relaxation Practices on Attention

The effects of meditation and relaxation techniques on attentional control have been extensively studied (Chiesa & Serretti, 2010; Ruedy & Schweitzer, 2010; Tang, Hölzel, & Posner, 2015; Zeidan, Gordon, Merchant, & Goolkasian, 2010). Meditation functions by inducing a particular attentional state, which aids in regulating both physiological and psychological processes. This refined attentional control enhances the effective allocation of attentional resources during initial processing stages, thereby enhancing subsequent cognitive processing (Malinowski, 2013; Zhou & Zafarani, 2020). Meditation practices have been shown to selectively influence the resolution of cognitive conflict between task-relevant and task-irrelevant stimuli, leading to enhanced cognitive performance (Zhou & Zafarani, 2020). Additionally, the cultivation of a non-judgmental acceptance attitude through mindfulness-based practices can modify the relationship between task-unrelated thoughts and task performance.

The Brief Mindfulness Meditation (BMM), based on classic mindfulness instructions used in the MBSR, composed of a 10-minute mindfulness exercise meticulously recorded by a experienced mindfulness instructor. This guided exercise prompted participants to conscientiously observe all facets of their present experience, encompassing thoughts and emotions, with an attitude of acceptance and curiosity. Participants were instructed to release any emerging mental phenomena and gently refocus their attention on the sensation of breathing in the present moment. The primary objective of this exercise was to cultivate a decentered disposition towards the experience, enabling participants to engage with their thoughts and emotions through the lens of mindfulness and acceptance. This led to a reduction in overall reaction times compared to conditions involving worry and free mind-wandering (Jankowski & Bąk, 2019). However, no discernible differences emerged among conditions in terms of the switch cost. These findings suggest that mindfulness practices may alleviate the allocation of attentional resources typically expended in suppressing task-irrelevant thoughts associated with anxiety, thereby enhancing the general efficiency of cognitive processes. Furthermore, brief mindfulness exercises may foster the adoption of a decentered perspective toward stressful experiences, thereby mitigating cognitive interference from intrusive processes (Jankowski & Bąk, 2019). The reciprocal relationship between attentional switching and mindfulness was also observed, indicating that proficient attentional switching may facilitate the induction and sustenance of the mindfulness state (Jankowski & Bąk, 2019). Brief mindfulness training can improve overall reaction times in a switching attention task, particularly in stressful conditions, by relieving working memory of its temporary load caused by irrelevant mental processes such as worry (Jankowski & Bąk, 2019). This indicates a specific beneficial effect of mindfulness practice on cognitive functioning, even in novice meditators.

Meditators tend to exhibit improved performance on the Stroop task compared to non-meditators, indicating both increased accuracy and quicker response times compared with a meditation-naive control group (Malinowski, 2013). Mindfulness interventions are found to enhance inhibition/executive control by promoting greater cognitive flexibility, attentional control, and self-regulation. Through practices such as focused attention and open monitoring, individuals learn to observe their thoughts and emotions without reacting impulsively. This heightened awareness and self-regulation contribute to improved inhibition and executive functioning (Verhaeghen, 2021). Scientific studies have revealed several key mechanisms through which meditation enhances attention. Firstly, meditation practices, such as mindfulness meditation, involve sustained attentional focus on a specific object or the present moment. This training in sustained attention helps individuals develop better attentional control and the ability to maintain focus over time (Tang et al., 2007). Secondly, meditation improves selective attention, allowing individuals to selectively focus on relevant information while filtering out irrelevant stimuli (Jha et al., 2007). This enhanced selective attention is attributed to the cultivation of mindfulness, which involves non-judgmental awareness of present-moment experiences. Mindfulness meditation reduces attentional bias towards negative or distracting stimuli, enabling individuals to redirect their attention more efficiently (Chambers, Lo, & Allen, 2008).

A comprehensive meta-analysis examining the impact of mindfulness meditation training on cognitive function, particularly focusing on attentional tests such as the Stroop and flanker tasks, revealed nuanced effects of mindfulness meditation training on attentional test performance, contingent upon factors such as session duration and training intensity. Specifically, Lin's analysis (Lin et al., 2022) highlighted notable findings regarding the efficacy of mindfulness meditation training. Direct comparisons between FA and open monitoring (OM) meditation indicated that both practices mitigated flanker interference on the Attention Network Task (ANT) following three training sessions. However, Lin also noted the existence of studies that did not report significant improvements in attentional test performance following mindfulness meditation training, underscoring the variability in outcomes across different investigations, which illustrates the complexity of the relationship between mindfulness meditation and attentional performance.

The discourse underscores that prevalent clinical mindfulness interventions, such as mindfulness-based stress reduction (MBSR) and mindfulness-based cognitive therapy (MBCT), commonly amalgamate both FA and OM techniques, often introducing FA practices preceding OM practices (Sumantry & Stewart, 2021). A meta-analysis of studies on the effects of mindfulness and meditation on attention and related cognitive variables found that interventions that included yoga practices led to lower and non-significant effect sizes, suggesting that yoga may diminish the overall efficacy of attention training in mindfulness programs (Sumantry & Stewart, 2021). Additionally, the presence of a yoga component in some interventions, such as Mindfulness-Based Stress Reduction (MBSR), demonstrates that MBSR interventions did not lead to a significant effect on attention, possibly due to additional psycho-education components and explicit advertising as "stress reduction", which may affect expectations and attract a specific population with different needs (Verhaeghen, 2021). In Caseda's analysis (Cásedas, Pirruccio, Vadillo, & Lupiáñez, 2020), only a small-to-medium effect favoring mindfulness training over control interventions in improving executive control was found. While individual effect sizes indicated positive impacts on working memory and inhibitory control, no significant effect was seen on cognitive flexibility. Furthermore, Caseda's meta-analysis delves into the dichotomy between two styles of mindfulness meditation practice: focused attention (FA) and open monitoring (OM) (Cásedas et al., 2020). The research indicates that the FA meditation style correlates with fewer errors in attention tests, while the OM meditation style generally results in superior performance.

1.8 Exploring the Effects of GI Practices on Attention

Conversely, there has been limited research examining the impact of Guided Imagery (GI) on attentional functions. Most research on Guided Imagery focuses on its application in hospital settings, often involving recovery, rehabilitation, and pain management. This emphasis is likely influenced by the historical context of Guided Imagery, which was initially studied primarily in relation to oncology patients (Beizaee et al., 2018; Carpenter, Hines, & Lan, 2017; dos Santos Felix, Ferreira, da Cruz, & Barbosa, 2019; Simonton, Matthews-Simonton, & Sparks, 1980; Vagnoli, Bettini, Amore, De Masi, & Messeri, 2019).

Within the literature, there exists research examining the combination of Guided Imagery with other relaxation techniques. Meditation practices, including Guided Imagery, have shown promise in enhancing cognitive functioning, executive function, and working memory, as well as improving mental health conditions such as anxiety and depression (Mitchell et al., 2021; Perich, Manicavasagar, Mitchell, & Ball, 2013; Shapiro, 2009; Williams et al., 2014; Vøllestad, Nielsen, & Nielsen, 2012). Research by Hudetz demonstrated that relaxation induced by Guided Imagery resulted in improved working memory performance and reduced state anxiety scores (Hudetz, Hudetz, & Klayman, 2000). The study found that relaxation induced by Guided Imagery significantly increased post-test working memory performance in healthy volunteers. The improvement in working memory scores was observed after a 16-minute relaxation session, with a significant increase in working memory scores in the Relaxation group compared to the Control group. The working memory scores increased by 30.2% after relaxation, while there was no significant change in the Control group. The increase in working memory scores in the Relaxation group was consistent, with an increase observed in 21 of 22 participants. The study also found a significant reduction in state anxiety. The findings suggest that working memory performance is enhanced by relaxation achieved through Guided Imagery.

1.9 Exploring the Effects of Relaxation Practices on Alpha Oscillations

Meditation has been found to have a positive impact on attentional processes, influencing various cognitive mechanisms and neural networks. It strengthens the neural pathways involved in attention, including the prefrontal cortex and parietal cortex, which play crucial roles in attentional processing (Lutz et al., 2008).

Scientific investigations have elucidated discernible variations in EEG (Electroencephalographic) activity contingent upon the specific meditation practices employed. The specific disparities in EEG activity between focused attention (FA) and open monitoring (OM) meditation practices are intricately tied to the underlying patterns of brain activity and cognitive processes characteristic of each modality of meditation. Empirical investigations have consistently demonstrated that FA meditation is correlated with elevated levels of alpha and theta power, alongside heightened alpha and theta coherence (Fingelkurts, Fingelkurts, & Kallio-Tamminen, 2015). Conversely, OM meditation has been associated with alterations in the mu rhythm of the human cortex, indicative of distinct cognitive states and neural processing mechanisms (Fingelkurts et al., 2015). These discernible distinctions in EEG patterns serve as tangible manifestations of the divergent neurophysiological effects elicited by FA and OM meditation practices on both brain activity and cognitive function.

It's important to clarify that the mu rhythm and the alpha rhythm are distinct forms of brainwave activity, each with its own neural correlates and functional implications. The mu rhythm manifests specifically in the sensorimotor cortex, whereas the alpha rhythm predominates in the occipital lobe (Fingelkurts et al., 2015). Both rhythms are intimately linked with diverse cognitive and physiological processes, underscoring the nuanced complexity of neural dynamics and their functional significance. Distinguishing EEG patterns between FA and OM meditation practices underscores the unique cognitive processes engaged during each modality. FA meditation initially directs the practitioner's focus towards developing attentional stability, clarity, and heightened awareness of their present mental state (Malinowski, 2013). Conversely, OM practice fosters moment-by-moment attentiveness to all facets of experience. EEG investigations have elucidated that FA meditation elicits augmented N2 and P3 components, indicative of intensified attentional resources and enhanced perceptual discrimination and conflict resolution mechanisms (Malinowski, 2013). In contrast, OM meditation is associated with heightened activity within regions implicated in the salience network, such as the anterior insula and cingulate cortex, which play crucial roles in emotion regulation. Consequently, EEG distinctions between FA and OM practices reflect the distinct attentional and emotional processes inherent to each form of meditation (Malinowski, 2013). These alterations signify heightened attentional regulation and enhanced perceptual discrimination and conflict resolution mechanisms, ultimately translating into enhanced performance on tasks such as the Stroop task (Malinowski, 2013).

The transition from beta to alpha brainwaves during meditation has been associated with higher-level cognitive processes (Hebert, Lehmann, Tan, Travis, & Arenander, 2005). Transcendental Meditation (TM) has exhibited a notable impact on alpha phase synchrony within the brain, characterized by heightened synchronization of alpha EEG activity, particularly evident between anterior and posterior regions. This increase of alpha phase synchrony during TM practice has been correlated with enhancements in cognitive performance and mind-body health. Furthermore, TM practice has demonstrated the capacity to enhance the signal-to-noise ratio of alpha and gamma oscillations, resulting in diminished gamma firing and heightened alpha flow. Moreover, TM has been linked with a transition from 'object referral' to 'self-referral' among advanced practitioners, signifying a shift in cognitive processing mechanisms (Hebert et al., 2005). These findings suggest that TM may facilitate the restoration of disrupted neural integration mechanisms and invigorate cortical fields in the brain, thereby fostering improvements in cognitive abilities.

Meditation has also been found to modulate the default mode network (DMN), a brain network involved in mind-wandering and self-referential thinking. Mindfulness meditation decreases DMN activity and disrupts the default mode of thought, reducing mind-wandering and enhancing present-moment attention (Hasenkamp & Barsalou, 2012). This shift from self-focused thinking to present-moment awareness contributes to improved attentional performance. Moreover, meditation practices impact attentional networks, such as the alerting, orienting, and executive control networks. These changes result in more efficient allocation of attentional resources and better performance in attention-demanding tasks due to the engagement of different brain regions and processes in FA and OM meditations. For instance, behavioral studies have shown that OM meditators exhibit superior performance on sustained attention tasks compared to FA meditators when the stimulus is unexpected, indicating a more distributed attentional focus in OM meditators. Furthermore, neuroimaging studies have demonstrated greater activity in neural circuitry associated with monitoring one's body state during OM meditation, as well as the engagement of emotion regulation processes located in the ventral prefrontal cortex (Lutz et al., 2008).

Most literature delves into the application of electroencephalography (EEG) as a tool for elucidating the neural underpinnings of meditation practices. It accentuates that engagement in meditation practices correlates with augmented power in theta and alpha frequency bands (Cahn, Delorme, & Polich, 2013; A. W. Moore, Gruber, Derose, & Malinowski, 2012).

Given the scarcity of literature exploring the influence of Guided Imagery (GI) on participants' attention levels, this study aims to bridge this knowledge gap in the field. There is great potential in utilizing this technique because, in contrast to meditation, GI can be tailored to address specific mental and emotional states, such as stress reduction, anxiety management, pain management, or improving performance. By integrating imagery that aligns with desired outcomes, individuals can access and cultivate the associated mental and emotional states more effectively. This level of customization can make Guided Imagery a useful tool for individuals with diverse needs and goals. However, despite the extensive use of Guided Imagery in various therapeutic contexts, there is limited research on its effects on brainwave activity, particularly compared to stress response regulation (Herman et al., 2003; McEwen & Gianaros, 2011).

Tables 1.2 and 1.3 provide a comprehensive analysis of diverse meditation techniques and their impact on attention control. Each meditation type is described, detailing its specific focus, cognitive benefits, effects on attention, performance on attentional tests, EEG findings, and practice methods. These insights illuminate the cognitive mechanisms underlying diverse meditation practices, suggesting their potential to enhance attentional abilities and cognitive performance.

Various meditation types are categorized in the table, including Mindfulness Meditation, Transcendental Meditation, Loving-Kindness Meditation, Yoga and Meditation, Open Meditation, Focus Attention Meditation, Vipassana Meditation, MBSR (Mindfulness-Based Stress Reduction), and Guided Imagery (GI). Each type is delineated based on its unique features and practices, such as promoting present-moment awareness, utilizing mantras, fostering compassion, combining physical postures with breathwork, encouraging broad awareness, and concentrating on specific objects.

The table reveals how each meditation type impacts attention control by improving focus, reducing distractions, and enhancing cognitive performance. Furthermore, the table evaluates the effectiveness of different meditation types on various atten-

Meditation Type	**Attentional Tests results**	**EEG Changes**	**FA or OM**
Open Meditation	Improved performance on Stroop Task and Flanker Task by reducing errors	Leads to changes in theta and delta brainwave activity associated with deep relaxation and heightened focus	OM
Focus Attention Meditation	Enhanced performance on Go/No-Go Task and Stroop Task by decreasing errors	Increases beta brainwave activity linked to alertness and concentration, improving attention control	FA
Mindfulness Meditation	Improved performance on Stroop Task and Anti-Saccade Task by reducing errors	Increases alpha and theta brainwave activity associated with relaxation and focus	FA
Transcendental Meditation	Enhanced performance on Flanker Task and Go/No-Go Task by decreasing errors	Produces coherent alpha and gamma brainwave patterns linked to heightened awareness and concentration	OM
Loving-Kindness Meditation	Improved performance on Attention Network Test by enhancing accuracy and speed	Increases gamma brainwave activity associated with positive emotions and heightened awareness	FA

Table 1.2: Overview of Relaxation Techniques and Their Effects on Cognitive Neuroscience. Compiled by Katarzyna Zemła based on scholarly references (Cahn & Polich, 2006; Lutz et al., 2008; Jha et al., 2007; Mellenthin, 2021; Travis & Shear, 2010; Zeidan, Johnson, et al., 2010; Zemla, Sedek, et al., 2023)

Meditation Type	**Attentional Tests results**	**EEG Changes**	**FA or OM**
Yoga and Meditation	Enhanced performance on Go/No-Go Task and Flanker Task by improving efficacy	Alters brainwave patterns towards a more relaxed and focused state, promoting attention and awareness	FA
Vipassana Meditation	Improved performance on Anti-Saccade Task and Attention Network Test by enhancing accuracy and speed	Increases theta and gamma brainwave activity associated with deep insight and heightened awareness	FA
MBSR (Mindfulness-Based Stress Reduction)	Enhanced performance on Go/No-Go Task and Attention Network Test by improving efficacy	Modulates alpha, theta, and gamma brainwave activity associated with relaxation, focus, and emotional regulation	FA
Guided Imagery	Enhanced performance on Stroop Task and Anti-Saccade Task by improving efficacy	Induces changes in alpha brainwave patterns associated with relaxation and heightened focus	FA & OM

Table 1.3: Overview of Relaxation Techniques and Their Effects on Cognitive Neuroscience. Compiled by Katarzyna Zemła based on scholarly references (Cahn & Polich, 2006; Lutz et al., 2008; Jha et al., 2007; Mellenthin, 2021; Travis & Shear, 2010; Zeidan, Johnson, et al., 2010; Zemla, Sedek, et al., 2023)

tional tests, such as the Stroop Task, Anti-Saccade Task, Flanker Task, Go/No-Go Task, and Attention Network Test. It demonstrates how each practice influences performance on these tests by enhancing accuracy, reducing errors, and improving overall cognitive function. Moreover, the table presents EEG results and changes associated with each meditation type, revealing brainwave activity patterns linked to relaxation, focus, heightened awareness, and emotional regulation. These findings offer insights into the neural mechanisms underlying the effects of meditation on attention control and cognitive performance. Additionally, the table specifies whether each meditation type involves focused attention (FA) or open monitoring (OM) practices, highlighting the cognitive processes engaged in each practice. Understanding the form of meditation practice provides insights into how different cognitive functions are cultivated and enhanced through mindfulness practices.

By exploring the unique characteristics and outcomes of each practice, the table succinctly summarizes their impact on the specified areas of interest, providing clear insights into cognitive neuroscience and mental well-being.

Based on the parallels drawn with focused attention (FA) and open monitoring (OM) practices in the table, the implications for GI are significant, particularly in terms of its potential impact on attention control, cognitive performance, and brainwave activity. GI shares similarities with FA practices in its capacity to enhance attentional control by directing focus towards specific mental images or scenarios. Similarly, akin to OM practices, Guided Imagery may lead to improvements in cognitive performance by fostering relaxation, reducing stress, and promoting attentional control. Moreover, Guided Imagery may induce changes in brainwave activity patterns associated with relaxation and heightened awareness, resembling effects observed in both FA and OM practices. Additionally, GI may offer therapeutic benefits for stress reduction, anxiety management, and cognitive enhancement, aligning with the holistic mind-body approach embraced by FA and OM practices. Overall, these findings underscore the potential of GI as a valuable tool for enhancing attention control, cognitive performance, and emotional regulation.

1.10 Potential benefits of Guided Imagery in Virtual Environments for Relaxation and Well-Being

The recent technological revolution has implemented new tools that provide computer-generated audio-visual displays and produce immersion in digital 3D environments. Literature in this field is growing. In "Virtual Reality–Guided Meditation for Chronic Pain in Patients With Cancer" (Fu et al., 2021), researchers verified whether a VR-guided meditation experience in patients with cancer-related pain would produce significant changes in EEG waveforms and affect the pain experienced during VR-guided meditation. The results of this study demonstrated the feasibility of EEG recording and subsequent data processing and analysis during VR experiences in patients using modern VR HMDs.

Eduardo Perez-Valero (Perez-Valero, Vaquero-Blasco, Lopez-Gordo, & Morillas, 2021) obtained results through EEG on twenty-three volunteers. Participants were subjected to stressful interactions alternating with relaxation phases. After quantitatively assessing the stress level through individualized regression algorithms, researchers developed stress classifiers that indicate regression models can quantitatively predict stress levels with noteworthy performance. Stress response regulation (Herman et al., 2003; McEwen & Gianaros, 2011; Gianaros, Onyewuenyi, Sheu, Christie, & Critchley, 2012) changes EEG brainwave activity. Specifically, alpha power (8–13 Hz) is thought to decrease due to its association with relaxation and inverse relation to cognitive activity (Klimesch, Doppelmayr, Schimke, & Pachinger, 1996), while beta power (13–30 Hz) is thought to increase in response to stress (Trakhtenberg, 2008) due to its association with information processing and anxiety (Stern, Gonzalez, Welsh, & Taylor, 2010).

Given the expansion of mental health problems and the significant increase in stress disorders caused by recent pandemics and wars, it is highly necessary to create solutions readily available to manage stress levels and support personal well-being. Rapid technological evolution, emerging datasets, and virtual reality offer the potential to build models and solutions that could support individuals in maintaining mental resilience while promoting cognitive functions.

According to attentional control theory (Eysenck et al., 2007), anxiety and worrying deplete attentional resources and reduce efficiency in cognitive tasks demanding effort, such as a switching task. While relaxation techniques offer wide-ranging physiological and psychological benefits, there is only a seminal work by Hudetz (Hudetz, Hudetz, & Reddy, 2004) that empirically demonstrated a significant augmentation of post-test working memory performance among healthy volunteers after a 16-minute Guided Imagery session. This improvement was associated with a marked reduction in state anxiety and changes in EEG activity. Despite the extensive body of research underscoring the beneficial effects of this methodology as a therapeutic intervention for life-threatening diseases (Simonton et al., 1980; Pelletier, 1977), Hudetz's findings stand alone in elucidating the correlation between Guided Imagery and brainwave activity (Hudetz et al., 2000). The notable lack of quantitative models illustrating the influence of Guided Imagery on brainwave activity is a gap in the current literature that this research aims to address. A recent manuscript on Convolutional Neural Networks (CNNs), derived from our research on Guided Imagery (GI) and currently under review for publication in Springer Nature Scientific Reports (Postepski et al., 2023), represents a significant advancement in the application of technology to support mental well-being. This research extends prior work on Guided Imagery (GI) by illustrating the efficacy of CNNs in discerning between mental workload and guided imagery states based on brain activity. The study highlights the substantial benefits of employing CNNs for the precise classification of these distinct cognitive states.

Applications of CNNs in EEG analysis include seizure detection, brain-computer interface (BCI) systems, sleep stage classification, emotion recognition, and cognitive workload assessment. Overall, CNNs enhance the capability to analyze complex EEG data, leading to more accurate and reliable results. Convolutional Neural Networks (CNNs) offer significant added value over typical machine learning classifiers, particularly in tasks involving image and spatial data which have several implications for the development of brain-computer interfaces (BCIs). Unlike traditional classifiers, which require manual feature extraction, CNNs automatically learn hierarchical feature representations directly from the raw input data. This capability is enabled by convolutional layers that apply filters to detect local patterns such as edges, textures, and shapes, which are then combined in deeper layers to recognize more complex structures. This leads to superior performance in tasks like image recognition, object detection, and image segmentation. Moreover, CNNs leverage parameter sharing and local connectivity, which reduces the number of parameters and computational complexity compared to fully connected networks. This efficiency, combined with their ability to generalize well across varied datasets, makes CNNs particularly powerful for handling large-scale, high-dimensional data, thereby enhancing accuracy and robustness in practical applications.

Convolutional Neural Networks (CNNs) are highly applicable to EEG (electroencephalogram) signal analysis. EEG signals, which are time-series data capturing electrical activity of the brain, can benefit from CNNs' ability to automatically extract and hierarchically learn relevant features. Here are some specific advantages:

- Spatial Feature Extraction: CNNs can capture spatial dependencies and patterns within EEG data, such as the relationships between different electrode signals. This is especially useful when EEG data is represented as 2D spatial maps (topographical maps), where CNNs can analyze the spatial distribution of brain activity.

- Temporal Feature Extraction: By applying convolutions over the time dimension, CNNs can effectively detect temporal patterns and trends within the EEG signals. This is crucial for tasks like detecting event-related potentials or distinguishing between different brain states.

- Noise Robustness: EEG signals are often noisy and subject to artifacts. CNNs can learn to focus on relevant features while ignoring noise, improving the robustness of the analysis.

- End-to-End Learning: CNNs enable end-to-end learning, where the model can be trained directly on raw or minimally processed EEG data. This reduces the need for extensive manual feature engineering, which is typically required in traditional machine learning approaches.

- Transfer Learning: Pre-trained CNNs on similar tasks can be fine-tuned for specific EEG analysis tasks, leveraging prior knowledge and improving performance even with limited data.

Through rigorous experimentation and comprehensive analysis, the research achieved an impressive classification accuracy of approximately 0.8, leveraging 20 sets of the most informative EEG signals for each state. This outcome underscores the strong capability of CNNs to capture and distinguish complex neural patterns associated with different cognitive states. By exploiting CNNs' abilities for automatic feature extraction and hierarchical learning, this research not only demonstrates a novel application of deep learning but also offers a promising methodology for enhancing the precision of cognitive state assessment. This advancement holds significant implications for the development of GI therapies and the improvement of brain-computer interface technologies.

The signals collected in our experiments illustrate that classification is achievable using both Generalized Linear Models (GLMs) and Convolutional Neural Networks (CNNs). This dual capability indicates the presence of distinct features and biomarkers within each signal, which can be precisely identified and attributed to specific classes of cortical brain activity. Although these features may be imperceptible to human observation, advanced data science methods can effectively discern them. The capacity of CNNs to detect such subtle and complex patterns underscores their potential to uncover intricate neural markers that distinguish different cognitive states, thereby enhancing the precision and reliability of brain activity classification.

Looking ahead, we envision that integrating VR technology with GLMs could enable patients to create vivid, positive experiences, thereby facilitating relaxation and promoting positive beliefs and attitudes toward their healing and treatment processes, or enhancing their overall well-being. This approach holds particular promise for individuals who lack easy access to specialized psychological support due to constraints such as time, financial resources, or geographical location.

Chapter 2

Research description and hypothesis

2.1 Research hypothesis

Based on the literature review, mostly related to meditation practices and their beneficial impact on human well-being, it was hypothesized that Guided Imagery (GI), a technique involving the creation of detailed mental images to induce relaxation and focus, holds promise for reducing stress levels and improving cognitive abilities. Drawing parallels with focused attention (FA) and open monitoring (OM) practices, Guided Imagery (GI) shares similarities in promoting relaxation, reducing distractions, and enhancing attention control. Given the documented efficacy of FA and OM practices in stress reduction and cognitive enhancement, Guided Imagery is hypothesized to similarly decrease stress levels and enhance cognitive abilities.

Alpha brainwaves, indicative of a relaxed and alert mental state, are expected to be influenced by GI due to its relaxation-inducing effects. Enhanced alpha wave activity, associated with improved cognitive functions such as attention, memory, and problem-solving skills, may mediate the association between the employment of Guided Imagery (GI) and the reduction in errors on attention tests resulting from Guided Imagery (GI) practices. Consequently, it was hypothesized that individuals after Guided Imagery (GI) intervention may experience heightened cognitive abilities and mental clarity through increased alpha brainwave activity.

Moreover, it is hypothesized that a brief session of Guided Imagery (GI) has the potential to reduce the number of errors in attentional tests, including the Stroop, Go/No-Go, and Anti-Saccade tests. This hypothesis is supported by evidence suggesting that GI enhances attentional control, cognitive performance, emotional regulation, and brainwave activity. Thus, the study aims to empirically investigate the effectiveness of Guided Imagery in improving attentional performance and inducing a relaxation state. Drawing from the literature on mindfulness and the core cognitive abilities of inhibition, shifting, and updating, which are cultivated through regular meditation practice, play a crucial role in supporting a mindful state (Holas & Jankowski, 2013). Studies have reported a relationship between mindfulness and performance on Go/No-Go tasks, with higher self-reported mindfulness scores associated with more accurate responses (Brown & Ryan, 2003; Feldman, Hayes, Kumar, Greeson, & Laurenceau, 2007; Keith, Blackwood, Mathew, & Lecci, 2017; Malinowski, 2013; A. Moore & Malinowski, 2009; Mrazek, Mooneyham, & Schooler, 2014; Schmertz, 2006).

Therefore, it is expected that the underlying mechanisms by which GI may enhance attentional processes can be attributed to several factors. Firstly, the relaxation and stress reduction induced by GI may contribute to improved attentional control, as stress and anxiety can negatively impact attention and cognitive performance. By inducing a relaxation state, Guided Imagery (GI) may alleviate distractions and promote a state of focused attention. Secondly, the visualization and mental imagery involved in Guided Imagery (GI) exercises can enhance cognitive flexibility and cognitive resource allocation. Engaging in vivid sensory experiences during Guided Imagery (GI) may train the brain to better allocate attentional resources, filter out irrelevant information, and maintain cognitive flexibility, which are crucial components of attentional control. Additionally, in light of the studies conducted by Kane and Engle (Kane & Engle, 2003), which highlight the role of "goal neglect" in error generation during the Stroop test, it is crucial to explore why changes are expected only in the number of errors and not in reaction times. Kane and Engle's findings suggest that individuals with higher working memory (WM) capacity exhibit fewer errors in the Stroop task compared to those with lower WM capacity (Kane & Engle, 2003). This relationship may extend to the Anti-Saccade task, where effective goal maintenance and resolution of competition from habitual responses are critical determinants of performance (Kane, Bleckley, Conway, & Engle, 2001). The ability to maintain task goals amidst competing responses is a key factor in reducing errors, an aspect that Guided Imagery might enhance through improved relaxation and attentional control.

The novelty of this research lies in its ability to showcase the potential of EEG signal classification with a Generalized Linear Model (GLM) for distinguishing between two distinct mental states, which could pave the way for developing innovative brain-computer interfaces tailored for therapeutic applications in the future.

Generalized Linear Models (GLMs) are highly versatile tools in machine learning and statistical modeling. They excel in handling various data types and distributions, making them adaptable to diverse classification tasks (Song, Langfelder, & Horvath, 2013). With GLMs, researchers gain interpretable insights into predictor-response relationships through easily interpretable coefficients. These models are computationally efficient, making them suitable for real-time applications. GLMs can be regularized to prevent overfitting and enhance generalization, while their feature selection abilities streamline model complexity and improve prediction accuracy (Dobson & Barnett, 2018). Additionally, GLMs provide probabilistic predictions and are robust to outliers and noise. They scale well to complex tasks and are relatively easy to implement and interpret, catering to users of all skill levels. Overall, the flexibility, interpretability, efficiency, and regularization capabilities of GLMs make them indispensable in classification tasks across various domains.

2.2 Research description

Initially, 60 participants were enlisted from the Computer Science student body at Maria Curie-Sklodowska University in Lublin. All participants were right-handed males aged between 17 and 24, with an average age of 20.38 and a standard deviation of 1.52. The decision to exclusively recruit male participants was based on the predominant male attendance in the Computer Science program at the university where the study was conducted, as well as reported disparities in electroencephalogram patterns between males and females. This approach aimed to achieve a relatively homogeneous response within the cohort. Participants were screened to ensure they did not have any chronic illnesses. They were required to disclose any significant health conditions such as chronic fatigue syndrome, cancer, or other long-term ailments, including mental disorders. Individuals with such conditions were automatically excluded from the participant pool being assembled.

The eligibility criteria for participants in this experiment specify individuals who are male, Polish-speaking, right-handed, healthy, and have short hair, aged between 17 and 24 years. They must have no record of chronic illnesses, not be currently using prescribed medication, soft drugs, or hard drugs, and should be able to attend study sessions without any technological needs. Participants were additionally requested to abstain from consuming alcohol or any medications for at least 72 hours prior to their involvement in the experiment.

The exclusion criteria encompass individuals who are below 17 or above 24 years of age, left-handed, possess long hair, do not speak Polish fluently, are suffering from serious or chronic illnesses, currently using prescribed medication, soft drugs, or hard drugs, have undergone medical treatment within one year preceding the study, or are unable to attend study sessions. Participants failing to meet the inclusion criteria or disclosing any significant illnesses, including mental disorders, were automatically excluded from the participant pool. Before engaging in the experiment, participants were briefed on EEG research and technology and provided consent to participate by signing an agreement.

The proportion of females engaging in computer science education remains limited, presenting challenges in forming a diverse participant pool for the experiment. We aim to ensure equal representation of left-handed and right-handed individuals, regardless of gender. Furthermore, it was noted that a considerable majority of female computer science students had lengthy hair. Notably, research has highlighted differences in electroencephalogram patterns between genders (Hanlon, Thatcher, & Cline, 1999; Jaušovec & Jaušovec, 2010), prompting our efforts to elicit a balanced response from the cohort.

The Fig. 2.1 presents structured sequence of steps, ensuring a systematic approach to data collection and analysis. Prior to the experiment, the study participants were required to provide informed consent, indicating their willingness to participate. The participants also completed various questionnaires, including the Scales of Helplessness and Anxiety of Contracting an Infectious Disease by Rydzewska and Sedek (Rydzewska, Pawłowska, Nielek, Wierzbicki, & Sedek, 2021), which were based on previous research on uncontrollability and adapted to the context of the COVID-19 pandemic. These measures aimed to assess the potential role of maladaptive emotions in impeding rational decision-making during the pandemic. The experimental cohort was then randomly divided into two sub-cohorts: Sub-cohort A, which consisted of 30 subjects exposed to relaxation GI technique, and Sub-cohort B, which consisted of 30 subjects assigned to perform the mental task. The EEG Lab, situated within the Department of Neuroinformatics and Biomedical Engineering, is outfitted with ad-

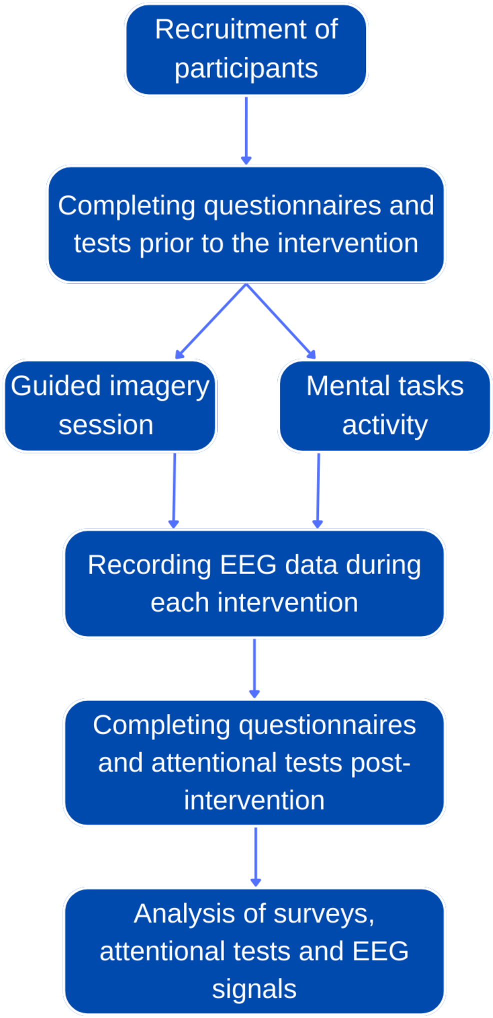


Figure 2.1: Experimental procedure schema

vanced equipment including a high-density array amplifier capable of recording brain electrical signals at a rate of 500 Hz, employing a 256-channel HydroCel GSN 130 Geodesic Sensor Net. This integrated system, crafted by Electrical Geodesic Systems, employs the Geodesic Photogrammetry System (GPS), which employs 11 cameras positioned in its corners to generate a precise model of the subject's brain based on its dimensions and shape. This setup enables accurate overlaying of computed brain activity onto the brain model. The amplifier operates in tandem with Net Station 4.5.4 software, while the GPS is managed by Net Local 1.00.00 and GeoSource 2.0. Eye tracking is facilitated by the SmartEye 5.9.7 system, enabling gaze calibration and removal of eye blinks and rapid eye movements. PST e-Prime 2.0.8.90 is utilized for designing the ERP experiments.

The Bioethical Committee of Maria Curie-Sklodowska University in Lublin, Poland, provided approval for all the experiments detailed below.

After undergoing pre-processing and eliminating data with poor quality, only participants who provided complete and good EEG quality recordings while meeting all exclusion criteria were included in the final analysis (Fig. 2.2. This resulted in a GI sub-cohort of 20 subjects and a mental task-engaged sub-cohort of 28 subjects. Participants were provided with information about EEG research and technology, and they signed an agreement for participation, as well as a declaration to ensure they fulfilled the inclusion and exclusion criteria. Additionally participants were also required to fill in their personal information and answer several questionnaires as outlined below: 1. The Scales of Helplessness and Anxiety of Contracting an Infectious Disease were developed by Rydzewska, K., and Sedek, G. (Rydzewska et al., 2021) as part of research materials from the SWPS University 2021. The Scale of Helplessness of Contracting an Infectious Disease is an adaptation of the Intellectual Helplessness Scale, which was originally designed to assess feelings of uncontrollability in educational settings. This earlier scale focuses on scenarios where individuals

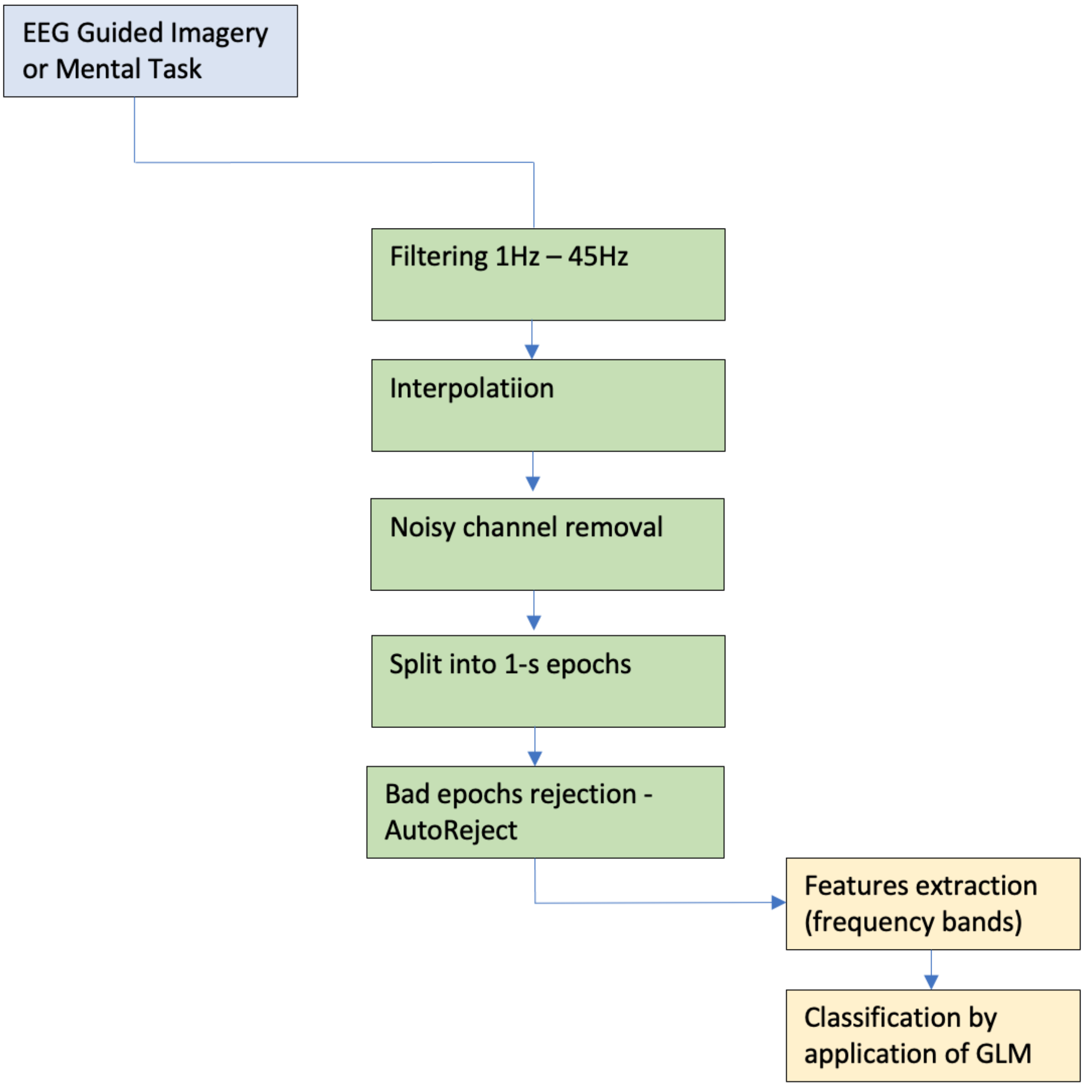


Figure 2.2: Data analysis pipeline (Zemla, Wojcik, et al., 2023)

persist in attempting to solve tasks they do not comprehend, leading to a sense of intellectual helplessness within that domain. In response to the COVID-19 pandemic, the researchers modified this scale to address the specific context of infectious diseases, particularly the pervasive feelings of helplessness and anxiety triggered by the pandemic's uncontrollable nature. The adaptation aimed to capture the emotional responses individuals might experience in the face of a rapidly evolving and uncertain health crisis. This adaptation is grounded in the analysis of the pandemic's initial exponential growth phase, as documented by Koczkodaj (Koczkodaj et al., 2020).

These measures are instrumental in highlighting the potential impact of elevated maladaptive emotions on rational decision-making during the pandemic. The Scale of Helplessness includes items such as "I feel helpless in the face of the possibility of contracting an infectious disease," while the Scale of Anxiety features items like "I am concerned when someone around me sneezes without covering their mouth." . Each scale consisted of ten items rated on a 5-point Likert scale, ranging from 1 (never) to 5 (always). These measures were used to indicate the potential role of high levels of maladaptive emotions in impeding rational decision-making during the pandemic.

2. The State-Trait Anxiety Inventory (STAI) is a self-report questionnaire designed to measure anxiety in adults. The STAI questionnaire consists of two separate scales: the State Anxiety Scale and the Trait Anxiety Scale. The State Anxiety Scale measures the level of anxiety that a person is experiencing in the present moment, and is therefore designed to assess the intensity of a person's emotional response to a specific situation (Spielberger, 1983). The scale contains 20 items that describe various emotional and physical symptoms of anxiety, such as ”I feel nervous” and ”I feel shaky.” Respondents rate each item on a four-point scale, from ”not at all” to ”very much so.” The Trait Anxiety Scale, on the other hand, measures a person's general level of anxiety across situations and over time. This scale contains 20 items that describe how respondent feels in general, such as ”I worry too much over something

that really doesn't matter" and "I feel calm." Again, respondents rate each item on a four-point scale. The STAI questionnaire is often used in medical and research settings to help identify people who may need treatment for anxiety (Spielberger, 1983). It can also help to measure the effectiveness of treatments designed to reduce anxiety.

3. Following both the GI and mental task sessions, participants underwent attentional tests to test the hypothesis that GI can enhance attentional control. Anti-Saccade tasks require participants to inhibit a reflexive saccade towards a visual target and instead make a deliberate saccade to a location opposite to the target. This task measures the ability to inhibit automatic responses and requires attentional control (Course-Choi, Saville, & Derakshan, 2017). The Anti-Saccade test attention control was designed according to the recommendations of the Antoniades protocol. In prosaccade trials, the object appears at the location of the cue, so the discrimination of stimuli is relatively easy. In Anti-Saccade trials however the identification of the object is more difficult, because it appears on the opposite side of the cue. The tasks were presented in a pseudorandom order, with control over the side of object presentation (left or right). After each trial, feedback on task accuracy was displayed on the screen. The main test consists of 4 blocks of tasks: Blocks 1 and 4: 12 prosaccadic tasks each Blocks 2 and 3: 24 antisaccadic tasks and 24 antisaccadic tasks with a mask Each block was followed by a 30-second break. The primary indicator in this task is the average percentage of correct responses for the antisaccadic blocks.

The numerical Stroop Test which is a variation of the classic Stroop test that uses numbers instead of words. The test is designed to create interference between the automatic response of reading the digits and the task of counting them, which requires more cognitive effort. In the study participants needed to count the number of digits on the screen and indicate the answer by pressing the appropriate numeric key. In congruent trials, the number of digits reflects their value: for example, three digits of value 3 so providing a correct answer 3 is cognitively facilitated. In conflicttriggering trials, the number of digits does not match their value: for example, three digits of value 2. To provide a correct answer, the participant should ignore the value of digit 2 and intentionally count their number. The test consists of 40 trials divided into 4 blocks:

- 5 congruent trials,
- 15 incongruent trials,
- 15 mixed trials (10 congruent and 5 incongruent in pseudo-random order),
- 5 congruent trials.

The main indicator in this test was the average percentage of correct answers. The test measures the ability to suppress automatic responses (response inhibition) and focus attention on the task at hand (Huang et al., 2019).

Go/No-Go tasks require participants to respond to one type of stimulus (the ”go” stimulus) but inhibit their response to another type of stimulus (the ”no-go” stimulus). This task assesses the ability to inhibit automatic responses and cognitive flexibility, as well as response inhibition and working memory (Meule, 2017). The tasks in the main block were arranged in a pseudo-randomized order while following the rule that No-go trials were preceded by 2 or 5 Go trials. The task requires pressing the down arrow key whenever a regular fish appears (Go trials) and refraining from pressing the down arrow key when a shark appears (No-go trials). The program waits for a response for up to 1.5 seconds. The interval between successive stimuli is set to one second. There are 150 trials in total, with a proportion of 80% Go trials and 20% No-go trials.

As a primary measure of Go/No-Go task performance on attention control was the percentage of correct responses for Go trials after No-go trials.

4. Furthermore, both prior to and following the GI and mental task sessions, the study participants were administered questionnaires developed by the research

team. These questionnaires encompassed various measures, including participants' self-reported levels of stress and relaxation on a 10-point scale and enabled the identification of emotions experienced by the participants before and after the GI and mental tasks experienced intervention.

To induce a state of relaxation, participants were seated in a comfortable armchair with earphones and listened to a 21-minute Guided Imagery (GI) recording prepared by a trained expert. The GI technique involves focusing on a positive mental image of a peaceful beach where they could feel safe and could relax their mind and body. They were asked to imagine themselves comfortably lying down on the warm sand, hear the waves that are hitting the sand and to experience the comforting warmth of the sun's rays on their face and the wind tenderly wrapping around their body. During the mental task, participants were asked to recall information, such as the capitals of European countries, zodiac signs, and the states of the United States of America. They were informed that their performance would be evaluated, and their reward would depend on the results. This task was chosen as it requires mental effort, leading to a high level of mental workload to simulate the everyday mental state. Both the Guided Imagery group and the mental task group underwent the same conditions in the experiment. This included listening to pre-recorded instructions for an equal duration. Additionally, two trained technicians supervised each experimental session, paying careful attention to technical aspects such as electrode placement, ensuring proper functioning, and managing the playback of the recordings.

Chapter 3

Research results and discussion

This study has several notable findings that contribute to the novelty of the research. Firstly, the analysis of brainwave data during Guided Imagery (GI) sessions revealed an increase in alpha power (Fig. 3.1), indicating a state of deep relaxation (Hebert et al., 2005).

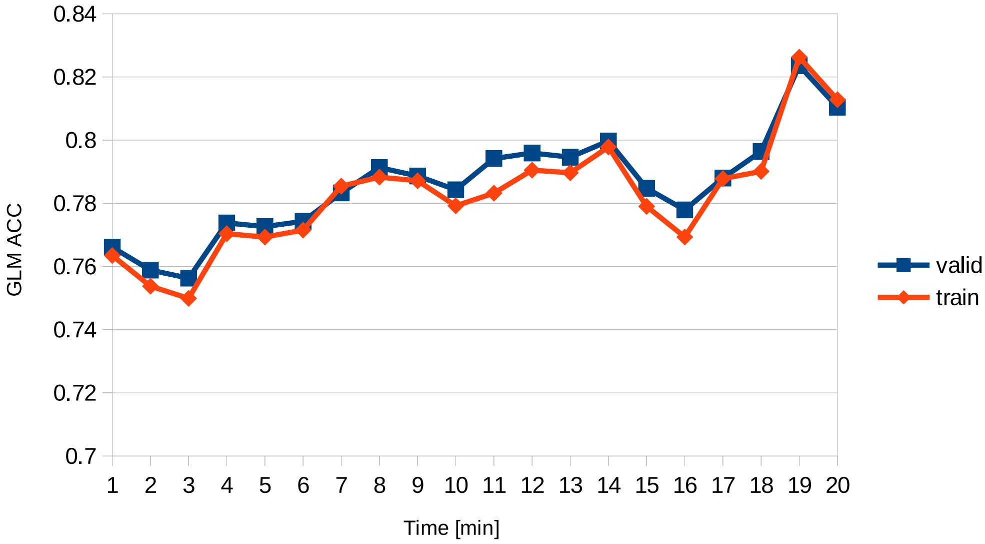


Figure 3.1: The 14th minute choice justification (Zemla, Sedek, et al., 2023)

An increase in alpha power in the brain is associated with a state of deep relaxation and reflects the current state of the art regarding the impact of relaxation techniques on brainwave activity. For instance this was evidenced in a study by Davidson (Davidson et al., 2003), which observed significant improvements in brain function and immunity among participants who underwent Mindfulness-Based Stress Reduction (MBSR) training. As well as during practices like Transcendental Meditation (TM), there is a notable increase in alpha power, indicative of restful alertness devoid of cognitive effort. This rise in alpha power during meditation suggests a state of profound relaxation and enhanced awareness, supporting the conventional notion of alpha activity as a marker of relaxation and the brain's idling state (Hebert et al., 2005). The results obtained are consistent with the existing scientific literature in this field and support the proposed hypothesis that Guided Imagery (GI) can induce relaxation and foster a relaxed mental state. In addition, alpha waves are associated with a state of relaxed alertness, which is conducive to improved cognitive functioning and attentional control (Praissman, 2008). Additionally, the study observed no significant differences in beta power between the GI group and the mental task group, suggesting that the relaxation induced by GI did not interfere with participants' ability to maintain attention and focus (Palacios-García et al., 2021).

The classification analysis using a general linear model (GLM) demonstrated high accuracy in distinguishing between the brain states of deep GI relaxation and engaging in a mental task (Fig. 3.1). The classifier's performance improved as the length of the signal input increased, indicating the effectiveness of using longer signal intervals for classification purposes. This finding highlights the potential of machine learning techniques, such as GLM classifiers, in accurately classifying brain states based on EEG data. The findings support the potential application of GI as an effective intervention for stress reduction and relaxation. Moreover, the study opens up possibilities for the development of brain-computer interfaces (BCIs) that utilize EEG recordings and machine learning classifiers to support therapy sessions and enhance the effectiveness of relaxation interventions. Brain-computer interfaces (BCIs) present a compelling option for a range of applications, due to their non-invasive nature, user-friendly design, and relatively low cost (Jiang, Lopez, Stieger, Greco, & He, 2021).

The results presented in Tables (Tab. 3.1 & Tab. 3.2) illustrate various psychological and neurophysiological measures comparing the Guided Imagery (GI) group and the Mental Task (MT) group. The analysis of these results in light of existing literature provides insights into the efficacy of guided imagery on emotional states and cognitive performance.

	Guided Imagery Group (N = 20)		Mental Task Group (N = 28)		Statistical Test		
Measures	**M**	**SD**	**M**	**SD**	**F**	***p***	**η^2**
Anxiety measures (pre-test)							
STAI Trait	45.00	7.91	45.93	33,117	0.12	n.s.	n.s.
STAI State	39.85	9.98	40.29	31,959	0.15	n.s.	n.s.
Motivational and affective measures							
Helplessness (pre-test)	18.00	5.48	17.3	4.94	0.41	n.s.	n.s.
Stress reduction (before–after)	2.25	5.27	1.00	1.52	**5.12**	**0.03**	0.102
Relaxation increase (after–before)	2.25	5.17	1.15	2.67	2.28	0.14	0.048

Table 3.1: Participants' Characteristics for Subjective Measures (Zemla, Sedek, et al., 2023)

The Tab. 3.1 shows the participants' characteristics for subjective measures in a study with two groups: Guided Imagery (GI) Group (N=20) and Mental Task (MT) Group (N=28). The measures include anxiety, helplessness, stress reduction, and relaxation increase. One-way analysis of variance (ANOVA) was conducted to test for notable differences between the groups. The significant reduction in stress observed in the Guided Imagery (GI) Group, compared to the Mental Task (MT) Group, underscores the efficacy of Guided Imagery (GI) as a stress management tool. This finding aligns with existing literature, which posits that Guided Imagery (GI) can induce relaxation by promoting positive mental imagery and reducing negative thoughts (Mellenthin, 2021). There are no significant differences between the Guided Imagery (GI) and Mental Task (MT) groups in terms of trait anxiety (STAI Trait) and state anxiety (STAI State) pre-test scores, indicating that the participants started with similar levels of anxiety. This is reflected in the non-significant p-values and F statistics. This outcome is consistent with research showing that pre-intervention measures are often similar across randomized groups, ensuring any post-intervention differences can be attributed to the intervention itself (Spielberger, Sydeman, Owen, & Marsh, 1999). There is a significant difference in stress reduction (F = 5.12, p = 0.03) with the Guided Imagery (GI) group showing greater reduction in stress compared to the MT group. This aligns with the findings that guided imagery is effective in reducing stress through relaxation and visualization techniques (Davidson et al., 2003). While there is an observed increase in relaxation in the Guided Imagery (GI) group, the difference is not statistically significant (p = 0.14). However, the trend supports the notion that Guided Imagery (GI) can enhance relaxation, which has been documented in previous studies (Jain et al., 2007).

Measures	Guided Imagery Group (N = 20) M	SD	Mental Task Group (N = 28) M	SD	Statistical Test F	*p*	η^2
Brain waves							
Alpha power (14th min)	0.25	0.13	0.17	0.12	**5.23**	**0.023**	0.105
Beta power (14th min)	0.08	0.03	0.07	0.03	1.23	n.s.	n.s.
Attention control							
Numerical Stroop task (% errors)	1.35	1.92	3.24	2.51	**8.06**	**0.007**	0.146
Anti-saccade task (% errors)	1.87	3.16	4.42	3.16	**7.31**	**0.010**	0.135
Go/No-go task (% errors)	7.33	6.72	8.85	5.93	0.70	n.s.	n.s.

Table 3.2: Participants' Characteristics for Brain Waves and Attentional Control Measures (Zemla, Sedek, et al., 2023)

The increase in alpha power (Tab. 3.2) at the 14th minute in the GI group (p = 0.023) suggests a state of deep relaxation and reduced cognitive activity, consistent with findings associating increased alpha activity with meditative states (Klimesch, 1999). This increase in alpha power aligns with current research and is correlated with the GI group's significantly fewer errors in the Stroop task (F = 8.06, p = 0.007), indicating improved attentional control. This finding aligns with research showing that relaxation techniques can enhance cognitive flexibility and inhibitory control (Mrazek, Franklin, Phillips, Baird, & Schooler, 2013; Tang et al., 2007). Fewer errors in the Stroop task are consistent with previous research linking mindfulness training to reduced activation of the brain's default network, which is associated with mind wandering (Kane & Engle, 2003). This enhanced ability to maintain focus on a single aspect of experience, despite interruptions, can prevent crucial task-relevant information from being displaced by distractions, ultimately leading to improved working memory (WM) capacity (Mrazek et al., 2013). Similarly, the Guided Imagery (GI) group performed better on the Anti-Saccade task, making fewer errors (F = 7.31, p = 0.01). The results indicate no significant difference in errors on the Go/No-Go task between the Guided Imagery (GI) and Mental Task (MT) groups, suggesting that the intervention's impact on inhibitory control might be task-specific or may require a longer duration to manifest significantly. This aligns with the findings of Lutz (Lutz et al., 2008), which demonstrate that different cognitive tasks can vary in their sensitivity to mindfulness and relaxation interventions. The lack of significant improvement in the Go/No-Go test might be attributed to its relatively lower cognitive demand, which may not be sufficiently challenging to capture the benefits of Guided Imagery (GI). As such, more complex tasks or extended intervention periods may be necessary to observe notable effects on inhibitory control.

Pearson's R correlations were conducted to examine the relationships be- tween different variables. The Tab. 3.3 presents the correlation coefficients, which suggest that higher Alpha Power at the 14th minute was significantly associated with better performance on the Numerical Stroop and Anti-Saccade tasks. The significant negative correlations between alpha power and the number of errors in the Stroop and

Variable	1	2	3	4	5	6	7
1. Alpha power 14 min	-						
2. Num. Stroop (% errors)	**−0.35 ****	-					
3. Anti-Saccade (% errors)	**−0.45 ****	**−0.38 ****	-				
4. Stress Reduction	**0.29 ***	−0.03	−0.22	-			
5. Helplessness	0.24	−0.12	−0.04	**0.29 ***	-		
6. STAI Trait	−0.12	0.10	0.27	0.10	**0.48 ****	-	
7. STAI State	0.14	0.01	0.12	0.21	**0.37 ****	**0.74 ****	-

Table 3.3: Correlations Between Measures. Note: * $p < .05$, ** $p < .01$. (Zemla, Sedek, et al., 2023)

Anti-Saccade tasks (r = -0.35 and r = -0.45, respectively) align with the literature indicating that increased alpha power is associated with enhanced cognitive performance. Alpha waves, typically observed in a state of relaxed wakefulness, are linked to better attentional control and reduced cognitive interference. Studies have shown that alpha activity facilitates inhibitory control, thereby improving performance on tasks requiring attention and cognitive flexibility (Klimesch, 1999; Jensen & Mazaheri, 2010).The positive correlation between alpha power and stress reduction (r = 0.29) corroborates research suggesting that relaxation techniques, which enhance alpha activity, are effective in reducing stress (Davidson et al., 2003). This reduction in stress likely contributes to improved cognitive performance by minimizing the cognitive load and emotional interference that stress can cause (Lupien et al., 2009). The negative correlation between the number of errors in the Stroop and Anti-Saccade tasks (r = -0.38) is supported by findings that both tasks measure aspects of executive function and attentional control. Effective management of attentional resources and inhibition of automatic responses are critical in both tasks, and improvements in one are often reflected in better performance in the other (Miyake et al., 2000). A reduction in error rate on the Stroop test is also indicative of the complex interplay among various cognitive functions. These include the capacity of our working memory to handle

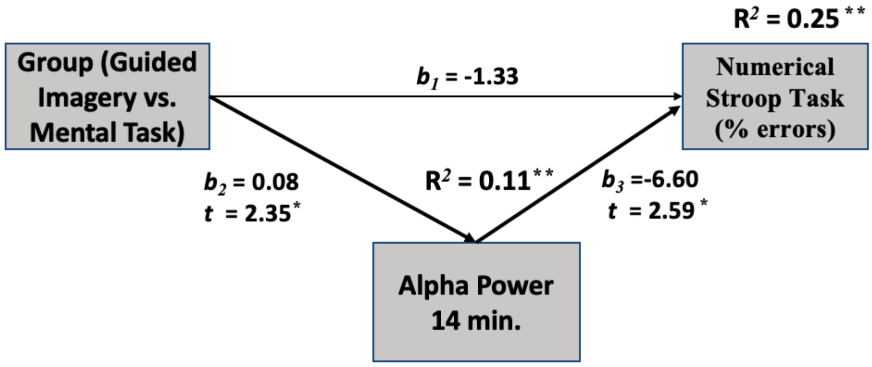


Figure 3.2: The effect of GI on reducing erroneous reactions in the Stroop test is mediated by Alpha Power at 14 minutes (Zemla, Sedek, et al., 2023)

information, our proficiency in directing attention, and our competence in managing conflicting demands (Kane & Engle, 2003). The strong positive correlation between STAI Trait and STAI State (r = 0.74) is consistent with the literature indicating that individuals with high trait anxiety are more likely to experience higher levels of state anxiety in stressful situations (Spielberger, 1983). These findings collectively support the hypothesis that Guided Imagery (GI), through its effects on alpha power, can enhance cognitive performance and reduce stress. The improvement in cognitive tasks can be attributed to better attentional control and reduced cognitive interference facilitated by increased alpha activity. Furthermore, the reduction in stress and anxiety highlights the potential of Guided Imagery (GI) as an effective intervention for enhancing mental well-being and cognitive function.

The study also employed mediation models (Fig. 3.2 & Fig. 3.3) to investigate the relationship between Guided Imagery (GI), alpha power, and cognitive performance, which provided understanding of the interplay between these variables. The mediational models elucidate the potential mechanisms through which Guided Imagery (GI) can affect cognitive performance and underscore the necessity for additional investigations to gain a deeper understanding of this domain. The significance of the t-values in the mediation models supports the relationships depicted, indicating

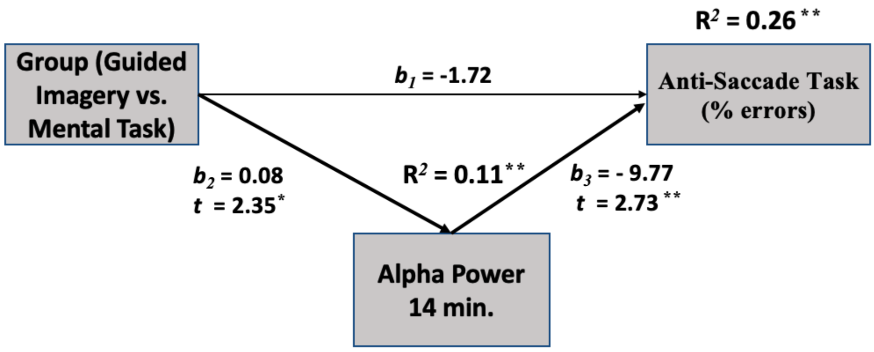


Figure 3.3: The effect of GI on reducing erroneous reactions in the Anti-Saccade test is mediated by Alpha Power at 14 minutes (Zemla, Sedek, et al., 2023)

that the observed coefficients are unlikely to have occurred by chance. These results are consistent with the findings of studies on mindfulness and relaxation techniques, which have shown that such interventions can lead to increased alpha activity, reduced stress, and improved cognitive function. For instance, Davidson (Davidson et al., 2003) demonstrated that mindfulness training can increase alpha power and enhance emotional regulation and cognitive performance. Thus, the current findings reinforce the notion that Guided Imagery (GI), by promoting a relaxed and focused mental state, can effectively enhance attentional control and reduce cognitive errors in demanding tasks. The findings also align with the work of Kane and Engle (Kane & Engle, 2003), who identified individual differences in working memory (WM) capacity as a significant predictor of performance on the Stroop task. Their research emphasized the importance of executive control and goal maintenance in selective attention, particularly in contexts that present competition between task goals and habitual responses. In the current study, Guided Imagery may have enhanced working memory (WM) capacity, allowing participants to better manage interference and maintain task goals in the Stroop and Anti-Saccade tasks. The dynamic interaction of memory maintenance and attention control, as proposed by Kane and Engle (Kane & Engle, 2003), is reflected in the significant improvements observed in the Guided Imagery (GI) Group. The attentional and executive components of the working memory

(WM) system likely drove these enhancements, supporting the notion that working memory (WM) capacity is crucial for maintaining representations of external stimuli, action plans, and task-relevant information in an accessible state.

The current study provides valuable insights into the selective enhancement of cognitive control and attentional regulation through Guided Imagery (GI). The better performance of the Guided Imagery (GI) Group in the Numerical Stroop and Anti-Saccade tasks highlights the potential of Guided Imagery (GI) to enhance higher-order executive functions, particularly in tasks involving significant cognitive load and complexity.

3.1 Research limitation

In interpreting the results, it is important to take into account the study's various limitations. The first is that the relatively small sample size used in this study might limit the generalizability of the findings to larger populations or other demographic groups. Because of this, care should be taken when extrapolating the findings to larger contexts. Additionally, the study's primary focus was on healthy male participants without any prior Guided Imagery (GI) session experience and no ongoing medical conditions. As a result, the results' applicability to other populations or people with particular medical conditions may be constrained. The study also focused mainly on the immediate results of the Guided Imagery (GI) session. Future studies should look into long-term benefits. When considered collectively, these limitations highlight the need for future research using larger and more varied samples, longer follow-up times, and more control groups. By addressing these methodological issues, a more thorough understanding of the efficiency and potential limitations of Guided Imagery can be attained, not only in the context of stress management but also in terms of improving attentional control test results. Such research will advance Guided Imagery's potential as a therapeutic intervention and offer insightful information about the broader cognitive advantages of the technique.

Chapter 4

Conclusion and Future Directions

The researchers' hypotheses were supported by the findings, as the Guided Imagery (GI) intervention resulted in increased alpha power and improved performance on attentional tests, particularly the Stroop and Anti-Saccade tests. The study's mediational model sheds light on the relationship between Guided Imagery (GI), alpha power at the 14th minute, and performance on attentional control tasks. The study contributes to the understanding of the interplay between Guided Imagery (GI), alpha power, and cognitive control, offering promising directions for future research on the applications of Guided Imagery (GI) in enhancing cognitive function and managing stress. The results align with existing theories on working memory (WM) capacity and attention control, reinforcing the critical role of WM in complex cognitive processes and its potential for improving executive function through targeted interventions (Lutz et al., 2008). Nevertheless, further research is necessary to validate these findings and delve into the underlying mechanisms of this relationship.

Additionally, the study's utilization of multi-sensor EEG signal classification and a General Linear Model (GLM) highlights the potential for developing new Human-Machine Interaction therapies. The efficiency of the classifiers increased with longer or more signal input, achieving accuracy rates of 68% with a 3-second interval, 78% with

1-minute intervals after 13 minutes, and approximately 92% for the entire 20-minute time range. Machine learning classifiers offer a dependable method for categorizing brain states during relaxation, where increased signal input duration or quantity correlates with higher accuracy. The study's results have implications for the development of interventions to enhance cognitive and emotional functioning, as well as the utilization of BCIs and real-time support systems. In addition CNNs could improved efficiency in data collection with the knowledge that a smaller subset of electrodes can be as effective as a larger set, the process of data collection for BCIs can be streamlined, reducing the complexity and cost of EEG setups. Future research should investigate the long-term effects of GI interventions, explore the relationships between cognitive and emotional measures, and further refine the application of machine learning in this context.

Overall, this study highlights the potential for combining traditional cognitive and emotional interventions with cutting-edge technology and advanced modeling techniques to create more effective and personalized treatments for a range of disorders.

The consistency of these findings with mindfulness research further validates the efficacy of Guided Imagery (GI) as a tool for cognitive enhancement and stress management. Further research in this area will advance our understanding of the sustained effects and interplay between cognitive and emotional domains, ultimately leading to the refinement of interventions promoting overall cognitive and emotional well-being. Future research should continue to explore the long-term effects of Guided Imagery (GI) and its applications in clinical settings to support individuals facing cognitive and emotional challenges.

Chapter 5

Contribution to the science

This study aims to fill a research gap by investigating the quantitative modeling of brainwave activities during GI. What sets this study apart from previous research is its focus on exploring brainwave patterns associated with GI relaxation, specifically the increase in alpha power, which indicates a state of relaxation and enhances attention test results. The study utilizes dense array electroencephalography (EEG) and machine learning techniques to classify and model the recorded brain signals obtained during Guided Imagery and mental workload tasks. By employing EEG signal analysis and general linear model (GLM) classifiers, this research presents a unique approach to understanding and differentiating brain states associated with Guided Imagery and mental workload. This methodology opens up possibilities for the development of therapy-oriented brain-computer interfaces, which can accurately discern states of relaxation from mental workload. These interfaces hold tremendous potential in providing computer-based interventions for anxiety and stress reduction. Accurately distinguishing brain states associated with relaxation can facilitate the creation of therapy-oriented brain-computer interfaces that deliver personalized interventions to individuals in need.

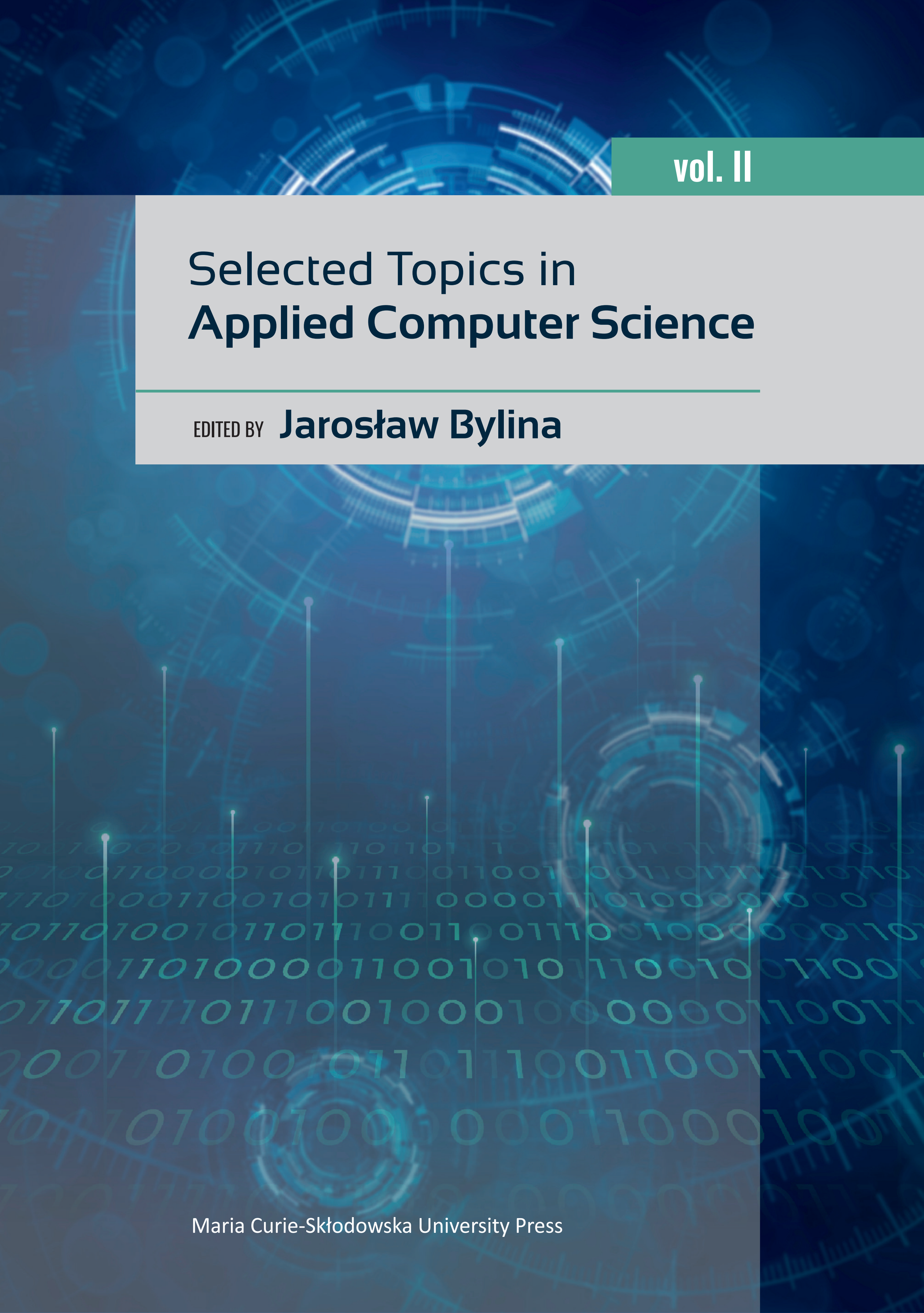
The study also expands on previous research that has examined the effects of relaxation techniques on attention and executive functions. While current literature has shown improvements in attentional control and executive function with mindfulness practices, there is a lack of research specifically focusing on the effects of GI on attentional tasks. By investigating attentional performance using established tests such as the Stroop task, Anti-Saccade task, and Go/No-Go task, the study verifies the impact of Guided Imagery (GI) on cognitive inhibition, selective attention, and response inhibition.

By elucidating the efficacy of GI in inducing relaxation and improving cognitive functions, this research sets the stage for exploring innovative treatment modalities tailored to combat the escalating incidence of anxiety-related disorders. Leveraging GLM models to enhance the effectiveness of GI interventions for individuals holds promise in optimizing therapeutic outcomes and meeting the diverse needs of those affected by anxiety and stress.

Chapter 6

A chapter and articles comprising the thesis

6.1 Investigating the lnfluence of Guided lmagery Relaxation on the Selected Electrophysiological Parameters of Human Body



vol. II

Selected Topics in Applied Computer Science

EDITED BY **Jarosław Bylina**

Maria Curie-Skłodowska University Press

Investigating the Influence of Guided Imagery Relaxation on the Selected Electrophysiological Parameters of Human Body

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1 Research background and the existing state of knowledge

Hypnosis, hypnotherapy and techniques like Guided Imagery (GI) are widely recognised as method supporting a wide range of therapies, including oncotherapies and mental disorders.

The primary objective of this paper is to present the literature review of the relaxation techniques appliance in supporting the health recovery programs is presented.

The secondary objective of this paper is to conduct the pilot study aimed at measurement of electrophysiological parameters: EEG brain cortical activity, pulse and blood saturation of the patient exposed to Guided Imagery hypnosis.

There are numerous examples of using hypnotherapy in the treatment of patients affected by HIV, ARC, or AIDS, among others [21]. For example, Auerbach demonstrated a meaningful reduction in physical symptoms associated with HIV, such as fever, pain, nausea, and a significant increase in activity and resilience in case of patients with ARC and AIDS who participated for 8 weeks in a group program that used biofeedback, imagery, and hypnosis, as compared to a control group [1]. Gochros used hypnosis in simultaneous individual and group therapy of seropositive patients in order to strengthen their ability to cope with the diagnosis and reduce the resulting stress [21]. His results showed a positive effect of hypnosis

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on anxiety and helplessness. Mentioned 8-week-long group program of Kelly, which included self-hypnosis and meditation training, was shown to help reduce stress and improve self-control and the daily quality of life of patients [14].

Newton and Marx used imaginal hypnosis in the Simonton approach with 4 men (10 individual sessions) and 22 men (10 group sessions) in order to improve the long-term survival of the patients [19]. Significant reduction of stress decreased anxiety related to their condition, and increased activity was observed in the case of patients who received the individual therapy.

The abovementioned Simonton method was first used in 1971 by Carl Simonton, an American physician and radiation oncologist. It had been then developed for more than 30 years. Simonton introduced the systematic use of psychotherapeutic interventions as a necessary extension of conventional cancer treatment [9, 29, 30]. Criticism of his studies and his reports on the positive therapeutic results of his approach to the treatment of patients affected by cancers initiated long series of standardized clinical trials. For instance, David Spiegel [33] confirmed the effectiveness of this approach.

Patients with distant metastases of advanced breast cancer were divided into two groups. Patients who additionally participated in a cognitive-behavioral therapy program as an adjunct to standard cancer therapy showed significantly better outcomes than patients in the control group who were only treated according to the current standards. Fawzy [8] came to similar conclusions regarding psychotherapeutic intervention in the treatment of patients diagnosed with malignant melanoma. And despite the clinically proven beneficial results of the use of cognitive-behavioral therapy increasing the level of coping with the situation after diagnosis, reducing the stress experienced, and having a beneficial effect on life expectancy after diagnosis has not resulted so far to attach such a standard of treatment support to all patients although it is known that the lifespan of the included participants in Fawzy's study was statistically twice as long [8]. The innovative concept to help patients using VR methods has the potential to change that and enable patients to support their treatment from the psychological edge. It is known and proven that when patients "think healthy" it supports recovery because they are able to:

- Enter a state of relaxation and relaxation as often as possible. Before and after, but also, if possible, during medical procedures.
- Put the brain into an alpha state and imagine positive scenarios of how my body, organs, and cells are healing under the influence of the applied therapy.
- Understand that these visualizations and alpha state are the way to support the immune system, as well as a pathway in its conditioning process.
- On the grounds of experiences (including those from virtual reality) build realistic and positive beliefs about one's condition, the medical procedures used, and the processes of treatment and recovery.

From the neuroscientific perspective adopted by Rossi [24], it is the patient's creative activity that generates, through the neuroplasticity of the brain, new neuronal connections so-called "miracle of healing based on the body-mind relationship." This deeply meaningful, internal creative mental process produces a hypnotic experience for problem-solving problems and healing. Healing is located within the patient. The therapist has no secret powers to control or heal. Patients heal themselves if they are lucky enough to receive the right "therapeutic suggestions" and psychological support which is described as "implicit heuristics of processing."

Research on implicit processing heuristics should take advantage of the current level of neuroscience and computer data processing and available technologies to build upon that [7]. For this purpose, our EEG study allows, among other things, the analysis of the amplitude and frequency of brain waves under hypnosis.

Several basic waves can naturally appear in the EEG recordings:

- Alpha waves (frequency 8–13 Hz, amplitude 30–100 μV) — are the rhythmic activity of the cerebral cortex in the 8–12 Hz range. This is one of the earliest observed structures (graphemes) of the EEG. The occurrence of the frequency of the rhythm alpha is attributed to the state of relaxation with eyes closed. Alpha waves are best seen in the posterior (occipital) leads, that is, from around the part of the cortex responsible for processing visual information. The alpha rhythm is of fundamental importance in EEG analysis of sleep. Although it does not occur during actual sleep it is indicative of the patient's "pre-sleep" wakefulness, and its disappearance signifies the transition from the waking state to shallow sleep. They are also attributed to a state of rest. Reduced alpha wave amplitude is noted in stressed individuals and those with an elevated state of anxiety.[1].

- Beta waves (frequency 12–30 Hz, amplitude >30 μV) In the beta spectrum, the following compartments are distinguished: slow beta waves (12–15 Hz), the proper intermediate beta band (15–18 Hz), and fast beta waves, with frequencies above 19 Hz. This unsynchronized neuronal activity characterizes the usual daily activity of the cerebral cortex in humans. The range of this frequency is observed during the state of active functioning, wakefulness, and alertness. It increases during logical thinking when attention is directed to cognitive tasks and the external world.[2]

- Theta waves (frequency 3.5–8 Hz) — activity in the frequency band from 3 to 7 Hz and a spread of several tens of μV. Characteristic theta waves occur, for instance, during the period of shallow sleep — it is assumed that during this time the assimilation and consolidation of learned content take place. Theta

[1]Low alpha (8–10 Hz) — is the range of waves with a frequency below the peak of alpha in the test person, with the eyes closed. With age, a decrease in the peak frequency of this wave. The higher peak frequency of this wave is found in more cognitively fit individuals. This frequency band is associated with meditation, with maintained calmness and relaxation. Low alpha is subject to diurnal fluctuations and we can note its higher amplitudes between the hours of 11 a.m. to 3 p.m. Significant fatigue of the subject can also affect the spectrum of this waveform [38]. High alpha (11–12 Hz or 11–13 Hz) — this frequency occurs when the state of high awareness of the environment. In this state, the brain can react quickly a precisely to changes in the environment. Waves of this band are a state of mental and physical calm, also known as the "zona" state. The mind is focused on the given moment "here and now," It is a state associated with high concentration and certainty of action [11].

[2]SMR sensory rhythm (13–15 Hz) — is observed in the sensory band of the cortex cerebral cortex. It is a spindle-shaped waveform. It determines the state of alertness, but without muscle tension muscles. It is a state in which high concentration is achieved. An understated amplitude of this wave may indicate problems with maintaining focused attention [11].

waves are the most common present brain waves during meditation, trance, hypnosis, intense dreaming, and intense emotions. It is mainly observed In the medial part of the front part of the cerebrum.[3]

- Delta waves (frequency 1–3 Hz) are high-amplitude activity with a low frequency (0–4 Hz) and a duration of at least 1/4 s. For practical purposes, the lower limit of frequency was assumed to be 0.5 Hz. Appearing during deep sleep, delta waves with an amplitude of more than 75 μV are called slow waves (SWA). Their appearance is due to the high synchronization of cortical neurons (a higher one is encountered only during an epileptic attack). Delta waves are also recorded during deep meditation in young children and the case of certain types of brain damage.[4]

- Gamma waves (frequency 25–100 Hz) — activity in the Hz frequency band is referred to instead referred to as high-frequency (high) gamma. The gamma rhythm accompanies motor activity and motor functions. Gamma waves are also associated with higher cognitive processes, including sensory perception, and memory, among others. It is speculated that gamma rhythms modulate perception and consciousness and that the greater appearance of gamma waves relates to expanded consciousness and spirituality [11].

Regardless of culture, race, upbringing, religion, and political views, all people with biologically intact brains experience stress in the same stereotypical way. The basis of such a stereotypical response to life-threatening situations are neurophysiological processes, related to the stimulation of the relevant areas of the central nervous system, which influences the immune system through the autonomic nervous system (sympathetic and parasympathetic), the endocrine system, and a direct effect on the limbic-hypothalamic system secreting immunomodulating neuropeptides [43]. This allows one to measure how even stagnant stress levels may change when applying stress reduction factors such as relaxation and visualization. Knowing that study conducted in 1987 by Kempthorne-Rawson, Persky, and Shekelle proves that pessimism and depression contribute to higher mortality among patients with cancer such methods to reduce its level should be included in standard treatment. In the 1950s, West, Blumberg, and Ellis showed that the rate of tumor growth is more related to psychological factors than to the degree of tumor differentiation found on histopathological examination [42].

Knowing how the body behaves in a relaxed or stressed state, it is possible to construct tests and use such measurements that will collect signals from heart, skin,

[3]Theta waves are associated with the extraction of information from memory and the ability to control reactions to stimuli. At this frequency, we are aware of our surroundings while the body is in a state of deep relaxation. They are associated with conscious observation of the environment (thalamic nuclei of the brain). In the state of theta waves, very creative thoughts, inspirations, and imaginations. This frequency helps recall memories, fantasies, and associations. In contrast, excessive amounts of theta waves have been reported in people with attention deficit disorder [11].

[4]Delta waves are the slowest of all brain waves. They occur during deep sleep and account for more than 50% of recorded brain activity. They have also been observed during transcendental meditation. Information received at this level is usually unavailable at the level of consciousness. Delta waves dominate the QEEG spectrum in infants up to 6 months of age. age. They are also recorded in brain damage and in brain tumor diagnoses [11].

or brain activity, so that researchers will be able to prove that hypnosis brought expected changes within the patient's body. For example, using measurements such as respiratory rate per minute, duration of inspiration and expiration, tidal volume (in ml), heart rate HR (in beats/minute), respiratory sinus arrhythmia RSA (difference between the maximum and minimum heartbeat interval, in ms,) logarithm of HFHRV-transformed power in the high-frequency band of heart rate variability, LF-HRV-transformed power in the low-frequency band of heart rate variability can quantitatively demonstrate how appropriately timed relaxation by modifying breathing patterns can put subjects into a relaxed state [39]. It is often assumed that cardiorespiratory changes induced by breathing instructions trigger a relaxation response [5]. Psychologically, breathing techniques usually induce an increased focus on internal sensations and comparatively disregard external stimuli [40]. Physiologically, most breathing exercises are designed to decrease sympathetic activity and increase the parasympathetic activity of the nervous system [2]. Results from a study at the University of Leuven strongly suggest that voluntary changes in the length of inhalation in comparison to exhalation are an important determinant of participants' reported relaxed states [39].

EEG studies on relaxation, on the other hand, show that a decrease in total power in the entire cerebral cortex during the relaxation state means that the brain activity of individuals during the relaxation process gradually decreases [36]. Physiological indicators of responses to relaxation introduced by Foster [17] include reductions in oxygen consumption, respiration and heart rate, as well as an increase in the production of alpha brain waves. Increased power of alpha and theta frequencies and interhemispheric synchronization, especially frontal alpha coherence [37] are usually considered as neurophysiological indicators of sensorimotor state and mental rest.

Regular relaxation practice can affect various physiological and psychological parameters related to aging, digestion, general well-being, and psychosomatic diseases. Consequently, there is a growing need to monitor physiological processes related to relaxation and stress response [25]. From the current literature on the subject, it can be concluded that deep relaxation is most often led to by slow, deep breathing at a frequency of 0.1 Hz.

In an article [25], the authors confirm that 6 breaths per min promote relaxation. In a book entitled "Relaxation, Meditations & Mindfulness" [31] mentions techniques to achieve a state of deep relaxation. These include Yoga classes, where progressive muscle relaxation and deep breathing occur. The author points out that the breath should be slow and even, and sometimes deep or shallow. Relaxation breathing has a rhythm in which the exhalation is slow and steady. At first, it may be deep and later shallow without effort. In general, relaxed exhalation takes twice as long (6 seconds) as inhalation (3 seconds).

We can divide the breathing process itself into:

- normal breathing (eupnoe) with a frequency of 0.25 Hz or 25 breaths per min,
- slow breathing (bradypnoe) with a frequency of 0.1 Hz or 6 breaths per min,
- fast breathing (tachypnoe) with a frequency of 0.5 Hz.

In the paper [4], researchers examined the effect of the respiratory cycle on EEG. W order to do so, they compared the spectral analysis of the EEG signal during inspiration and expiration.

Normal, slow, and fast breathing were checked. The researchers noted that during inhalation with normal breathing, delta wave activity in the parietal region and total activity in the frontal region. With fast breathing during inspiration, there is a decrease in beta wave activity in the central region and activity in the theta in the posterior temporal and occipital regions. Compared with the EEG in eupnoe, bradypnoe and tachypnoe, there was a decrease in the spectral power of all spectral bands except delta during faster respiration rates and vice versa, with a significant difference found mainly between bradypnoe and tachypnoe, less frequently between eupnoe and tachypnoe.

In another article [10], researchers examined the effect of breathing patterns on EEG activity. They conducted the study on healthy participants. Each examined had to breathe deeply and slowly (6 breaths per min), hold their breath, and breathe quickly and deeply (30 breaths per min). The EEG signal was read from the frontal, parietal and occipital regions of the head. The researchers detected an increase in alpha and beta activity in the frontal region during deep and slow breathing. In contrast, there was a process of decrease in the activity of these waves in all regions during breath-holding. In the case of slow and deep breathing, only alpha decreased.

The pace of speech we know from studies on the subject is that a healthy person utters about 10–15 sounds per second. In the case of uttering a greater number of them, i.e. 20 (or more), understanding the speaker's speech is much more difficult.

Three modes of speaking tempo can be distinguished [34]:

- lento (slow, slow tempo),
- moderato (moderate),
- allegro (fast, English quick tempo).

Usually, texts are spoken at a moderato tempo. For longer speeches, as a rule, there are different speaking tempos. Their interplay is a characteristic feature of spoken language. a person pronounces an average of 10–15 vowels per second. The pronunciation of 21 vowels per second is on the verge of speech intelligibility. The time taken to pronounce syllables and vowels is measured in milliseconds. For example, the duration of shortness consonants is about 40 milliseconds, while the duration of an average syllable is 200–300 milliseconds. In fast speech, the average duration of a vowel is 60–70 milliseconds, and in slow speech — 150–200 milliseconds. If only in connection with this knowledge, it would be necessary to adjust the recording in such a way that the speaker speaking to the patient pronounces the voices at a rate that is within the 150–200 millisecond range. Science is studying also the effect of sound on our mood. Human responses to sound are experienced on several different levels: physical, mental, cognitive, and behavioral [38].

Nevertheless, there are still relatively few studies that document the relevance of this factor, especially at the level of interpersonal communication. Instead, we know that one of the elements of effective psychotherapy is empathy, which also expresses itself in non-verbal ways [17]. That's why it's so important to lean into the importance of speech characteristics, to consciously use the right sounds, tone of voice, or tempo, as this translates into the reactions of physiological and mental reactions that are induced in the recipient especially by using VR tools.

In the professional exchange of information, for example, in the psychotherapeutic process, communication takes place simultaneously at the verbal and nonverbal levels. Verbal communication without nonverbal transmission is practically nonexistent. Thus, there are areas where the way information is communicated is of great importance not only for the quality of the future relationship such as patient and doctor but also to trigger a psychosomatic response, which can be translated into the functioning of the patient's immune system. Indeed, it should be pointed out that, for example, an appropriate tone of voice can allow for stress reduction when communicating a diagnosis. A study from 2011 funded by the National Cancer Institute shows that nonverbal information revealed in a lower tone of voice and a slower rate of speech gives the impression of being more empathetic [18]. This has a direct bearing on the patient's mental state, who feels better understood and embraced with compassion [56]. And although more research has been conducted within the realm of verbal empathic communication it is indicated that non-verbal based on the tone of voice and rate of speech is equally important [28]. How the message is conveyed is of particular importance important in the case of oncology patients, who face high levels of stress, tension, and fears for their lives as they face dealing with the disease [22].

Another study that confirms the importance of voice tone and tempo on levels of relaxation was conducted in 2006 in the biofeedback research laboratory of the Department of Behavioral Medicine and Psychiatry at West Virginia University. It investigated the effectiveness of progressive relaxation training (PRT) on selected vocal characteristics and its impact on the treatment process [15]. In the study [15], the goal was to see how the volume, pitch, timbre of the voice, and intensity of speech could affect the therapeutic process. As early as 1979, Ryan and Moses showed [26] that a soft, melodious voice can translate into treatment effectiveness. In addition to subjective assessment of the relaxation state or the subjects' perception of speech characteristics, participants in the experiment had their heart rate (HR) measured, and EMG signals were collected, verifying the electrical function of the electrical activity of muscles and peripheral nerves. The intensity of the voice conducting the relaxation training was measured in decibels, the tone of voice in Hz, and the number of syllables per second of tape was calculated. The results of the study clearly show that a voice that lowered and became more monotonous during the session caused a significant reduction in EMG levels (electromyography) which translated into a reduction in muscle tension. At the same time, the subjective feelings of the subjects confirmed that the way they used, and modulated their voice in therapy had an impact on their level of relaxation.

Muscle tension, like other vegetative autoregulatory processes (body temperature, heart rate, blood pressure, intestinal motility, etc.) sweat secretion cannot be controlled consciously. Since 1972, more than 1,500 articles have been published in professional publications on GSR (cutaneous-galvanic response) is considered the most popular method for studying the phenomena of human psychophysiological phenomena [3]. Although GSR is an ideal measure for tracking emotional arousal, it is unable to reveal the emotional valence i.e., the quality of the emotion. The true power of GSR unfolds when combined with other data sources to measure complex dependent variables and provide a complete picture of emotional behavior. Often, this test is performed in experiments involving games, or reactions to images or videos presented [32]. This opens the way to seek quantitative answers based on skin responses to further questions related to the mode of communication used in the VR treatment program so that the solution can best serve to reduce the patient's stress level and support relaxation, to enhance the healing processes.

In research on voice analysis during discussions of bad news in oncology [18], the author also states that no study analyzed verbal content, speech analysis, and other related nonverbal behavior, and notes that this is a desirable research topic. Most studies focus on listening to music and not the voice itself, these studies show that relaxation music (e.g. Bach, Vivaldi, Mozart) results in a slowing of the heart rate [6].

Music can strongly evoke and modulate emotions and mood, as well as changes in heart function, blood pressure (BP), and respiration. In the various studies on the effects of music on the heart, there is a wide variety of methods and quality, but can be established that: heart rate (HR) and respiratory rate (RR) are higher in response to exciting music compared to calming music [16]. W a study of music therapy to help treat children with cancer, music reduced pain ratings, heart rate, respiratory rate, and feelings of anxiety, during lumbar puncture, when children had headphones with music, they felt less pain and were calmer and relaxed during and after the procedure. All of these children wanted headphones with music when they next undergo the procedure [20]. This proves that listening to music already has its applications during medical therapies. There are not many publications that talk about listening to the voice itself, but studies show that people already in the womb can recognize the mother's voice, which has been observed to reduce the fetal heart rate [41]. Hypnosis (a recording with a slow breathing command) has also been shown to reduce heart rate, even in stressful situations such as dental procedures [6].

Thus, the VR treatment program's assumption that listening to a calming voice reduces heart rate appears to be true [23], and the creation of a device to monitor heart rate and attempt to lower it using a voiceover and guided relaxing trance will make it possible to study more closely how initially rhythmically spoken words at the same rate as the initial heartbeat rhythm heart rate affects the heart rate after the words are slowed down and whether the patient will calm down.

“The real power of understanding lies in not allowing our knowledge to be fettered by what we do not know.” — stated Ralph Waldo Emerson — which is why it is important to continue research and see what combinations between the breath, the voice of the speaker, the rate of speech will bring the best effects thru VR treatment.

2 Experiment description

The EEG laboratory (Fig. 1) in the Department of Neuroinformatics and Biomedical Engineering at the Maria Curie-Skłodowska University in Lublin is equipped with apparatus that allows the precise study of bioelectrical changes occurring in the patient's brain thanks to an EGI dense matrix amplifier (Electrical

Figure 1: EEG laboratory in the Department of Neuroinformatics and Biomedical Engineering at Maria Curie-Sklodowska University in Lublin, Poland

Geodesic Systems, Oregon, USA), to which caps equipped with 256 electrodes (HydroCel GSN 130 Geodesic Sensor Nets) can be connected. The lab offers the ability to record signals at frequencies up to 1000 Hz (with simultaneous measurements by all 256 electrodes). The laboratory has a GPS photogrammetric station with GeoSource software that enables the application of source localization algorithms and the precise generation of a model of the subject's brain.

For a trial approach aimed at designing a research protocol to answer the formulated questions formulated by the Ordering Party, a relatively simple test was proposed involving putting the patient (in this case, the Department Head) into a state of deep relaxation by a qualified therapist (Katarzyna Zemla, M.Sc, SWPS doctoral student, Master of Cognitive Behavior BIK), and then recording the electrical activity of his brain in four main activity bands (alpha, beta, theta, delta) and measuring his heart rate and hemoglobin saturation throughout the entire study.

Hemoglobin saturation (SpO2) in the blood was measured using a Kermed A310 pulse oximeter. Heart rate was measured using a Xiaomi Mi Band 5. After the test, the patient was measured at a photogrammetric station. During the main part of the study, only the patient and the therapist were in the laboratory room, and twilight prevailed. The lab technicians were present only during the preparation of the patient and during the geodetic measurements. The study conducted on December 11, 2020, lasted 30 minutes.

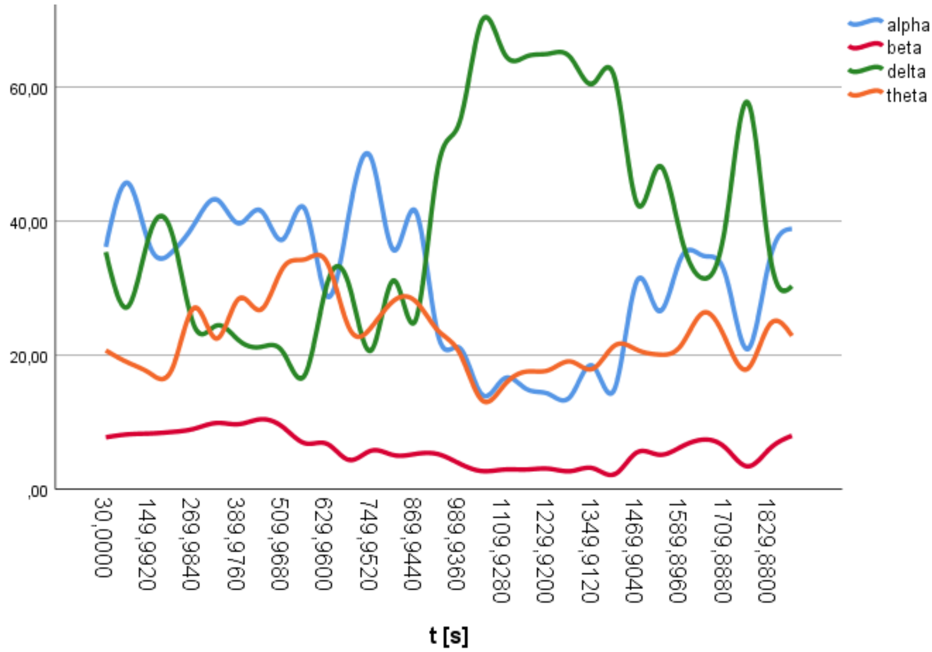

Figure 2: Percentage of each wave during the experiment

3 Experiment description

The percentage of each band of the electrical activity of the patient's cerebral cortex during the test is shown in Fig. 2. Changes in the subject's heart rate during the experiment are presented in Fig. 3. A graph of changes in hemoglobin saturation is shown in Fig. 4.

We can observe an increasing and then relatively high proportion of delta waves starting from about 870 seconds of the test (see. Fig. 2). This is accompanied by a relatively high proportion of alpha and theta waves at the beginning of the study with a low level of beta waves throughout the experiment. Starting at 870 seconds of the survey, there is a slight decrease in the contribution of alpha and theta waves as delta activity increases (see. Fig. 2).

The increase in delta activity is accompanied by an increase in pulse rate (see. Fig. 3) and a slight but observable increase in hemoglobin saturation (SpO2) (see. Fig. 4).

As is well known, the more than 50% contribution of delta waves to brain activity is associated with the phase of deep meditation or deep sleep. It can be presumed that an increase in the patient's delta brain activity above 60% in the study was related to the therapist's attempt to by the therapist to obtain the phenomenon of dreaming in sleep, which took place at that time. time. On the other hand, the increase in pulse rate may indicate a correlation between this phase with the visualizations occurring in the patient's state at the time of the

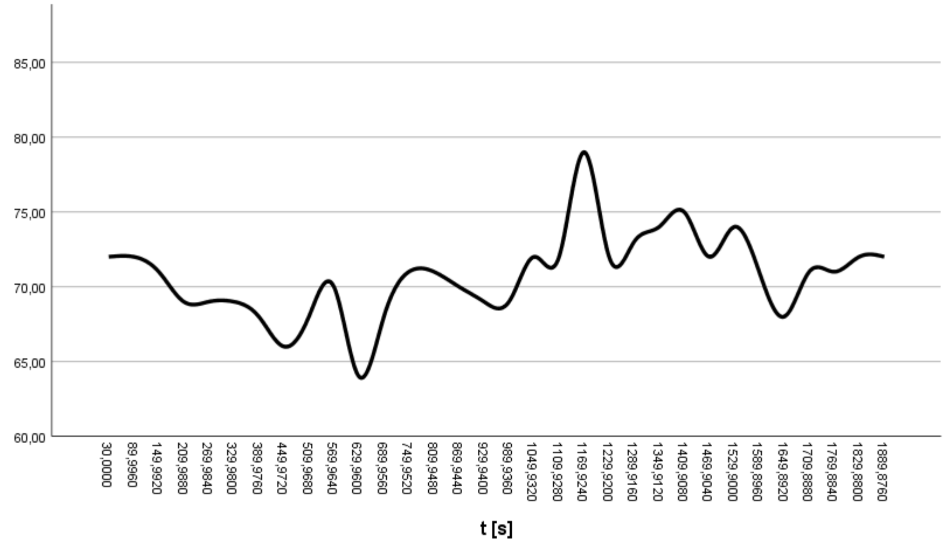

Figure 3: Pulse variations during the experiment

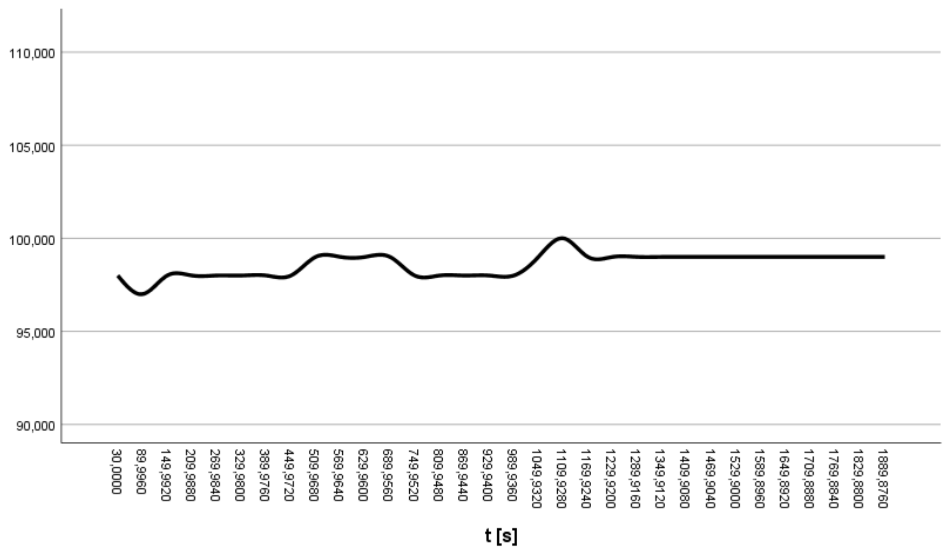

Figure 4: Hemoglobin saturation level (SpO2) during the experiment

examination. Theta waves at relatively high levels (about 30% on average) confirm the state of hypnosis into which the patient was put, also a state associated with shallow sleep; their decrease starting at 870 seconds indicates a rapid transition of the patient into a state resembling deep sleep.

It is difficult to conclude a single case. However the study pilot study was intended to show that we have the possibility of reliable quantitative recording of the electrical activity of the cerebral cortex and combined with a relatively simple to use and inexpensive apparatus, we can look for correlations of this activity with pulse rate and blood hemoglobin saturation (SpO2). After connecting the galvanometer it will be possible to study stress levels changes.

4 Recommendations

4.1 The rationale behind the VR treatment concept

The originators of the project rightly point out that the poor mental state in which most oncology patients find themselves reduces their quality of life during and after the various stages of treatment and can delay the processes of treatment and recovery. Therefore, the goal of the VR treatment program is to improve the mental state of patients so that they can experience positive emotional states even if they do not have the exceptional mental strength and are not able to control their thoughts and negative states. Patients by putting on the goggles and headphones could create new experiences and build positive beliefs and attitudes toward the healing and treatment process and reinforces and stabilizes a positive emotional state. In contrast, the poor mental state in which most oncology patients prolongs and impedes the treatment and recovery processes, and above all, reduce the quality of life during treatment. VR solution would allow the solution even if we face difficulty with access to specialized psycho-oncological help.

Carl Simonton's therapy, mentioned earlier, is based on activities in the following areas: behavior (relaxation, creating new habits), beliefs (changing unhealthy beliefs to ones that give us peace of mind and energy to act), emotions (maintaining hope, dealing with emotions that harm us, learning to cope with everyday stressful situations), spirituality, communication with supportive people (building a support system, learning healthy communication), and physicality (diet, movement, the role of play in the recovery process).

The many assumptions not only of selecting the most effective method but also of how to combine it with technology, which today offers the possibility of creating virtual worlds, cause many hypotheses and unknowns to arise, which need to be further investigated and verified. The relaxation module itself, for it to respond to changes in the patient's physiological state as well as the therapist must be designed to respond to his breathing, pulse, or measuring changes in the skin's electrical resistance.

When relaxation is led by a therapist, he or she often sees and adjusts the guidance of the body relaxation and visualization to the patient's breathing. The hypnotherapist can see when the patient's chest is on the inhale and lowers on the exhale. So the open question remains how to map this alignment when the patient puts on the goggles and receives instructions from the VR treatment program in the most effective way?

4.2 Recommended research

To extend current phase of conducted pilot study it is recommended to proceed with further steps such as:

- In-depth research on the susceptibility of patients to relaxation intervention depending on a set of variables obtained from psychological questionnaires: anxiety, depressiveness, introverted, extroverted personality types which may determine natural attitude toward diagnosis.
- Conducting experiments to build classifiers capable of suggesting the most appropriate pace and method of conducting the relaxation intervention.
- Conducting experiments to test the performance of the constructed clarifiers.

This is the initial stage of our project.

Depending on the personal properties and external influence each patient can have an individual ability to be exposed to relaxation, varying in time and other conditions.

In future, it will be useful to investigate the pace at which particular subjects get into a deep state of relaxation. It was only our expectation that they ought to do this in around 14 minutes. However, each individual can be characterised and most probably is by his own pace. Plotting their state in the function of time would be recommended.

Using machine learning classifiers is expected to find application in the classification of biomedical signals towards therapy support citedylkag2021pilot, mikolajewska2014non. Machine learning tools and algorithms have been used for decades also for lots of disorders diagnostics like alcoholism or depression [27, 12] and others [47] using new measures like those defined in [46] as well as advanced modelling of biological systems behaviour [35] including diagnostics purposes [13, 44, 45].

Acknowledgements

Research presented herein was supported by the City of Lublin as a part of cooperation of Lublin City Hall and Maria Curie-Sklodowska Univeristy towards pilot study for VRMed project. The Authors would like to thank Ms. Ewa Lewandowska and Mr. Marek Rudziński of VRMed for fruitful discussions, inspiration and possibility of working together on new ideas.

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6.2 Modeling of Brain Cortical Activity during Relaxation and Mental Workload Tasks Based on EEG Signal Collection

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Special Issue
Artificial Intelligence in Life Quality Technologies

Edited by
Prof. Dr. Piotr Prokopowicz, Prof. Dr. Katarzyna Węgrzyn-Wolska and Dr. Maciej Piechowiak

MDPI

https://doi.org/10.3390/app13074472

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Article

Modeling of Brain Cortical Activity during Relaxation and Mental Workload Tasks Based on EEG Signal Collection

Katarzyna Zemla [1], Grzegorz M. Wojcik [2,*], Filip Postepski [2], Krzysztof Wróbel [2], Andrzej Kawiak [2] and Grzegorz Sedek [1]

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Abstract: Coronavirus disease 2019 (COVID-19) has caused everything from daily hassles, relationship issues, and work pressures to health concerns and debilitating phobias. Relaxation techniques are one example of the many methods used to address stress, and they have been investigated for decades. In this study, we aimed to check whether there are differences in the brain cortical activity of participants during relaxation or mental workload tasks, as observed using dense array electroencephalography, and whether these differences can be modeled and then classified using a machine learning classifier. In this study, guided imagery as a relaxation technique was used in a randomized trial design. Two groups of thirty randomly selected participants underwent a guided imagery session; other randomly selected participants performed a mental task. Participants were recruited among male computer science students. During the guided imagery session, the electroencephalographic activity of each student's brain was recorded using a dense array amplifier. This activity was compared with that of a group of another 30 computer science students who performed a mental task. Power activity maps were generated for each participant, and examples are presented and discussed to some extent. These types of maps cannot be easily interpreted by therapists due to their complexity and the fact that they vary over time. However, the recorded signal can be classified using general linear models. The classification results as well as a discussion of prospective applications are presented.

Keywords: guided imagery; relaxation; EEG; GLM

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Citation: Zemla, K.; Wojcik, G.M.; Postepski, F.; Wróbel, K.; Kawiak, A.; Sedek, G. Modeling of Brain Cortical Activity during Relaxation and Mental Workload Tasks Based on EEG Signal Collection. *Appl. Sci.* **2023**, *13*, 4472. https://doi.org/10.3390/app13074472

Academic Editors: Alexander N. Pisarchik and Alexandros A. Lavdas

Received: 12 January 2023
Revised: 24 March 2023
Accepted: 27 March 2023
Published: 31 March 2023

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1. Introduction

A handful of relaxation techniques are used to reduce stress, and they have been the subject of scientific investigation for decades [1–3]. Relaxation techniques can be widely used for stress reduction in the post-COVID-19 reality and may become one of the most often used psychological or pharmacological therapies. Although the COVID-19 pandemic has been associated with physical conditions, social, psychological, and economic consequences are also being observed globally; changes to normal life may lead people to suffer from a higher degree of mental health problems, including fear of infection, uncertainty, stress, anxiety disorders, sleep problems, mood disorders, and suicidal ideation [4–6].

Many methods, including relaxation training [7–9], biofeedback [9], hypnosis [10,11], and various forms of yoga meditation [12,13], have been successfully used to reduce tension and anxiety. Guided imagery is one of the world's oldest healing resources [14]. Interest in the practice of mental imagery and the role of imagination in health and well-being has dramatically increased, as mental imagery has become a popular approach for treating a wide variety of psychiatric and medical concerns and for enhancing sports performance [15]. In medical and scientific research, guided imagery has been defined by some researchers "as the internal experience of a perceptual event in the absence of the actual external stimuli", where imagery refers to the awareness of sensory (physical) and perceptual (cognitive) experiences [16]. Some guided imagery is also referred to as guided visualization [17,18]. Guided imagery (GI) is a cognitive, behavioral, mind–body, evidence-based technique that is employed to manage pain, including cancer pain, which affects and/or modifies the psychophysiological state of patients [19]. GI affects a variety of systems, including the respiratory, cardiovascular, metabolic, and gastrointestinal systems, and immune responsiveness. Psychoneuroendocrinoimmunology (PNEI) research has demonstrated that the psychological response to GI can modulate the activity of the hypothalamic–pituitary–adrenal axis, reducing the stress response and increasing the feeling of well-being. Central and immune nervous system modulation through the release of enkephalins, endorphins, cholecystokinin, and cortisol may be among the mechanisms mediating these effects [20].

Meditation practices are associated with enhanced executive function and working memory together with improvements in mental health condition severity (e.g., anxiety, depression, and eating disorders [21–25]. Hudetz's finding is that relaxation from 16 min of guided imagery significantly increased post-test working memory performance in healthy volunteers, and this improvement paralleled a significant reduction in the state–anxiety scores as a result of relaxation training and EEG activity [26].

No findings other than Hudetz's on guided imagery and brainwave activity have been published, even though this is one of the oldest relaxation techniques, and many studies have proven its positive impact during life-threatening disease treatment [27,28]. This research is novel in this field as our main objective was to revise if quantitative modeling can predict if and when participants enter a relaxation state, meaning alpha power increases and beta power decreases, when exposed to guided imagery. Our original prediction was that the pattern of brainwave activity reverses in comparison with that reported the existing research on brainwave activity during stress response regulation [29,30]. Changes in the EEG brainwave activity, specifically alpha power (8–13 Hz), are thought to decrease because of the association of alpha power with relaxation, with an inverse relationship with cognitive activity [31], whereas beta power (13–30 Hz) is thought to increase in response to stress [32] due to its association with information processing and anxiety [33]. A number of studies have confirmed this hypothesis: oscillatory changes in frontal alpha (decrease) and beta (increase) power during or after applying stressors such as exam stress [34] and during cognitive stressors such as the Stroop task [35]. In contrast, studies on relaxation techniques such as meditation techniques have noted increased alpha power with the use of these techniques [36–39]), which has been linked to improved cognitive performance [40,41].

In this research, we aimed to check if guided imagery (in comparison with a mental workload task) could produce the predicted and observed changes in brainwave activities (mainly an increase in alpha power and, to some extent, a reduction in beta power) as observed using dense array electroencephalography, and whether such differences could be modeled and then classified using a machine learning classifier. This study is innovative because such pattern was found using a guided meditation technique but not (with the exception of [42]) applying the relaxing technique of guided imagery.

With technological advances, new tools can provide computer-generated audio–visual displays and produce immersion in digital 3D environments. The literature in this field is expanding. In a study [43], the authors verified whether a VR-guided meditation experience for patients with cancer would produce significant changes in EEG waveforms and whether any changes would occur in the pain experienced during VR-guided mediation. This study demonstrated the feasibility of using EEG recordings in exploring neurophysiological changes in brain activity during VR-guided meditation and its effect on pain reduction. Such modern brain imaging techniques are valuable as they provide data for the verification of the computational models focusing on understanding the relationship between cognition and the brain [44]. Eduardo Perez-Valero created a stress level classification via electroencephalography (EEG) and machine learning on twenty-three volunteers [45]. Participants were subjected to stressful interactions alternating with phases where they were able to relax. After quantitative assessment of the stress level through individualized regression algorithms, the researchers developed stress classifiers that indicated that regression models could quantitatively predict stress levels with noteworthy performance.

In this study, we wanted to verify whether obtaining such quantitative prediction but on relaxation level is possible. Therefore, the two main objectives of the study were: to record and visualize the brain cortical activity of subcohorts exposed to guided imagery relaxation and mental tasks and to train a general linearized model (GLM) classifier to classify the recorded signal into one of the two classes: relaxation or mental workload. Such a classifier might allow high-probability identification of when a patient is in a state of relaxation, which will provide the opportunity to create computer-based devices that can help with anxiety and stress reduction.

For this study, 60 computer science students at Maria Curie-Sklodowska University in Lublin, were recruited for a randomized trial. Half of the randomly selected students were exposed to relaxation, as recorded by an experienced trainee in guided imagery, whereas the remaining students solved mental tasks.

In this paper, we show that it is possible to build a general linear model that can be used to accurately distinguish the state of a participant's brain. Although the GLM is a commonly known classifier, its application to EEG signal analysis is uncommon. The novelty of this study is the evidence of the possibility of classifying two mental states using EEG signal classification and a GLM, which, in the future, may lead to the construction of new therapy-oriented brain–computer interfaces.

2. Materials and Methods

2.1. Cohort Recruitment

We recruited 60 participants from among computer science students at Maria Curie-Sklodowska University in Lublin.

They were 60 right-handed men aged from 17 to 24 years; the average age was 20.38 with a standard deviation of 1.52.

The experimental cohort consisted of two subcohorts:

- A: 30 subjects who were exposed to relaxation.
- B: 30 subjects who were asked to perform a mental task.

2.2. Inclusion and Exclusion Criteria

To ensure the repeatability of the study, we defined the inclusion and exclusion criteria as follows.

2.2.1. Inclusion Criteria

The age of participants should be in the range of 17–24, as this was the typical age of the computer science students at the university where the experiment was conducted. They should be short-haired, right-handed men, because long hair hinders the recording of signals without noise. The number of women studying computer science was still low, so building a balanced cohort including an equal number of left-handed and right-handed men and women for the experiment would have been difficult. In addition, most of the women studying computer science had long hair. Notably, differences have been reported in electroencephalograms between men and women [46,47], and we wanted to have a relatively equal cohort response.

We also assumed that, due to lateralization, handedness may play a significant role in classification. All students selected for the cohort were white men of Polish nationality or citizenship, fluently speaking Polish.

Another inclusion criterion was being healthy; not using prescribed medication, soft drugs, or hard drugs; with no medical treatment history in the one year following the study; and with no chronic diseases, including chronic fatigue syndrome, cancer, or any other diseases or mental disorders. Participants had to have the ability to attend study appointments with no technological requirements.

The participants were nonsmokers and asked not to consume alcohol or any medications at least 72 h before participation in the experiment.

2.2.2. Exclusion Criteria

Mean younger than 17 or older than 24 years, left-handed, or with long-hair and all women were automatically excluded from the cohort recruitment process due to the reasons explained above.

Participants that did not fluently speak the Polish language were excluded from the cohort because the GI session was recorded in Polish and mental tasks were formulated in Polish. To replicate the study, we suggest choosing the same language for GI sessions, mental tasks, and cohort members.

Candidates even nonseriously ill (flew, cold, running nose, etc.) were excluded from the cohort recruitment process.

Candidates taking prescribed medications, soft drugs, or hard drugs were excluded from the cohort recruitment process.

Candidates with a medical treatment history in one year following the study or with chronic diseases, including chronic fatigue syndrome, cancer, or any other diseases or mental disorders diagnosed were excluded from the cohort recruitment process.

Candidates who could not attend study appointments could not be included in the cohort.

2.3. Information for Participants

Before participating in the study, participants received information about EEG research and technology and their role in the project. Then, they signed the agreement for participation.

They also filled and signed the declaration fulfilling the requirements of inclusion and exclusion criteria in an attempt to determine that none of our participants suffered from chronic diseases. The participants were asked to declare serious diseases such as chronic fatigue syndrome, cancer, and all other chronic diseases, including mental disorders. If they declared so, they were automatically excluded from the cohort.

2.4. EEG Recordings

All EEG recordings were obtained using a 256-channel dense-array EEG amplifier with a HydroCel GSN (geodesic sensor net) 130 manufactured by Electrical Geodesic Systems (EGI) (500 East 4th Ave. Suite 100, Eugene, OR 97401, USA), and the sampling frequency was 250 Hz. The amplifier worked with Net Station 4.5.4 and SmartEye 5.9.7 software for gaze calibration and eye-blinking or saccadic artifact removal. The laboratory was also equipped with a geodesic photogrammetry system (GPS), which was operated using Net Local 1.00.00 and GeoSource 2.0. The event-related potential (ERP) experiments were designed in PST e-Prime 2.0.8.90.

2.5. Deep State of Relaxation

During relaxation, each participant sat in a comfortable armchair with earphones on his head, and the relaxation procedure was played through the earphones from the record. The record was prepared by a trained expert, which is the typical method used in guided imagery (GI) [48–50]. Guided imagery is a relaxation technique that involves dwelling on a positive mental image or scene. The length of the record was 21 min and 7 s; however, for this research, the first 21 min were taken into consideration. It was assumed that sooner or later, each member of this subcohort would be relaxed enough to manifest brain cortical activity that could be classified.

2.6. Mental Task

During the mental task, participants were asked to recall facts from memory as much as possible. These facts included the capitals of European countries, zodiac signs, and the states of the United States of America. The participants were told that they would be asked to write these answers down after the experiment and that their reward was dependent on the results. We assumed that such a task would require some mental effort, leading to a high level of mental workload.

2.7. Preprocessing Pipeline

The collected signal was preprocessed using the following procedures and parameters set on Net Station software: filtration with 1 Hz high-pass and 45 Hz low-pass filters. Then, the standards for Net Station interpolation and noisy channel removing algorithms were applied as well as automatic and, in some cases, manual artifact removal. Then, the signal was divided into 1 s epochs, and noisy epochs were removed in Net Station using the AutoReject toolbox. See Figure 1.

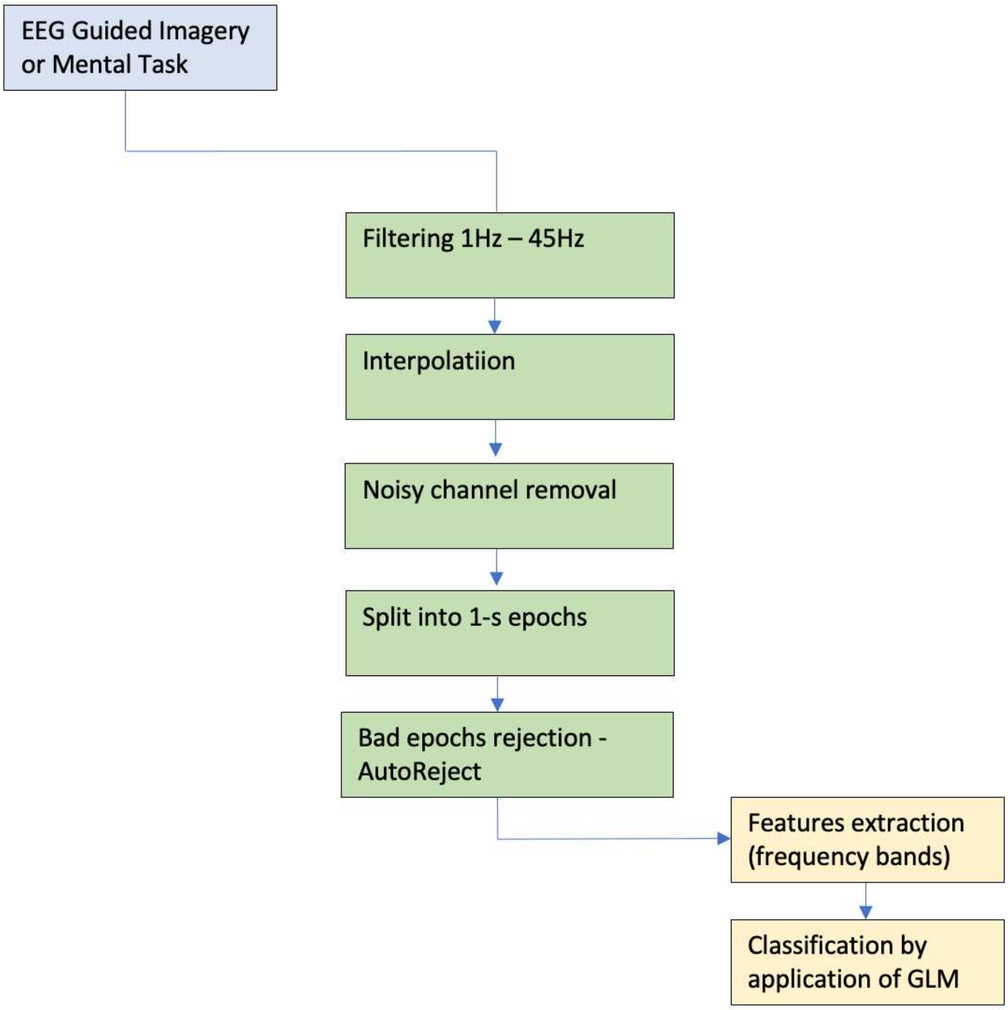

Figure 1. Data analysis pipeline for the experiments. For details, see the text.

3. Results

Examples of 3-min time interval plots are presented in Figure 2 for a selected student in subcohort A, who experienced GI relaxation, and in Figure 3 for a student in subcohort B, who performed the mental workload task. These maps, however, are too similar and cannot be easily interpreted using the naked eye. For example, in Figure 2 (state of relaxation), we can see increased activity in the β band, and in Figure 3, considerably α-band activity can be observed. However, Figures 2 and 3 present particular student cases and a specific 3-min time interval from a 21 min recording of brain cortical activity. As expected, plots such as those in Figures 2 and 3 change over time, and quickly analyzing them would be difficult.

Nevertheless, differences in activity are visible, even though they are not easily interpretable. An appropriately trained machine learning classifier can be used for this task.

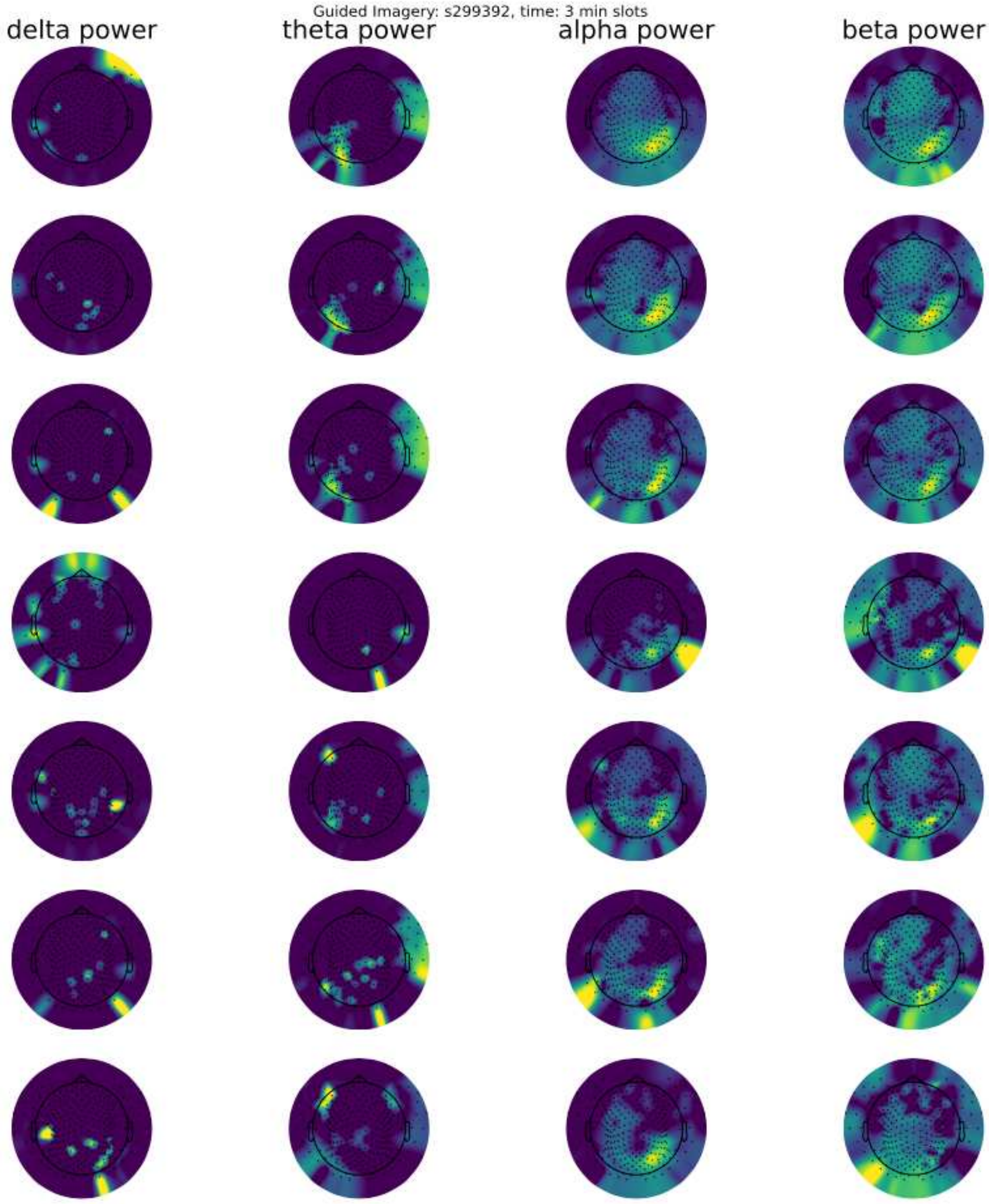

Figure 2. Power activity in the δ, θ, α, and β bands for participant s299392 exposed to guided imagery. Each row, one-by-one, represents a 3-min slot, for 21-min in total. For details, see the text.

Machine Learning Data Analysis

The signal was classified using generalized linear models (GLMs) using the implementation included in the h2o library available for Python. Model tests based on different time windows were conducted in Python version 3.7.5.

The quality of the classification was tested for the same time intervals in the two data groups.

Group A: Signals with less than 10% erroneous epochs; Group B: all signals included in the dataset (60 signals). According to the documentation of the h2o library, using generalized linear models, balanced data were not required.

In the case of Group B, the signals removed due in noisy epochs were interpolated by the library mentioned above.

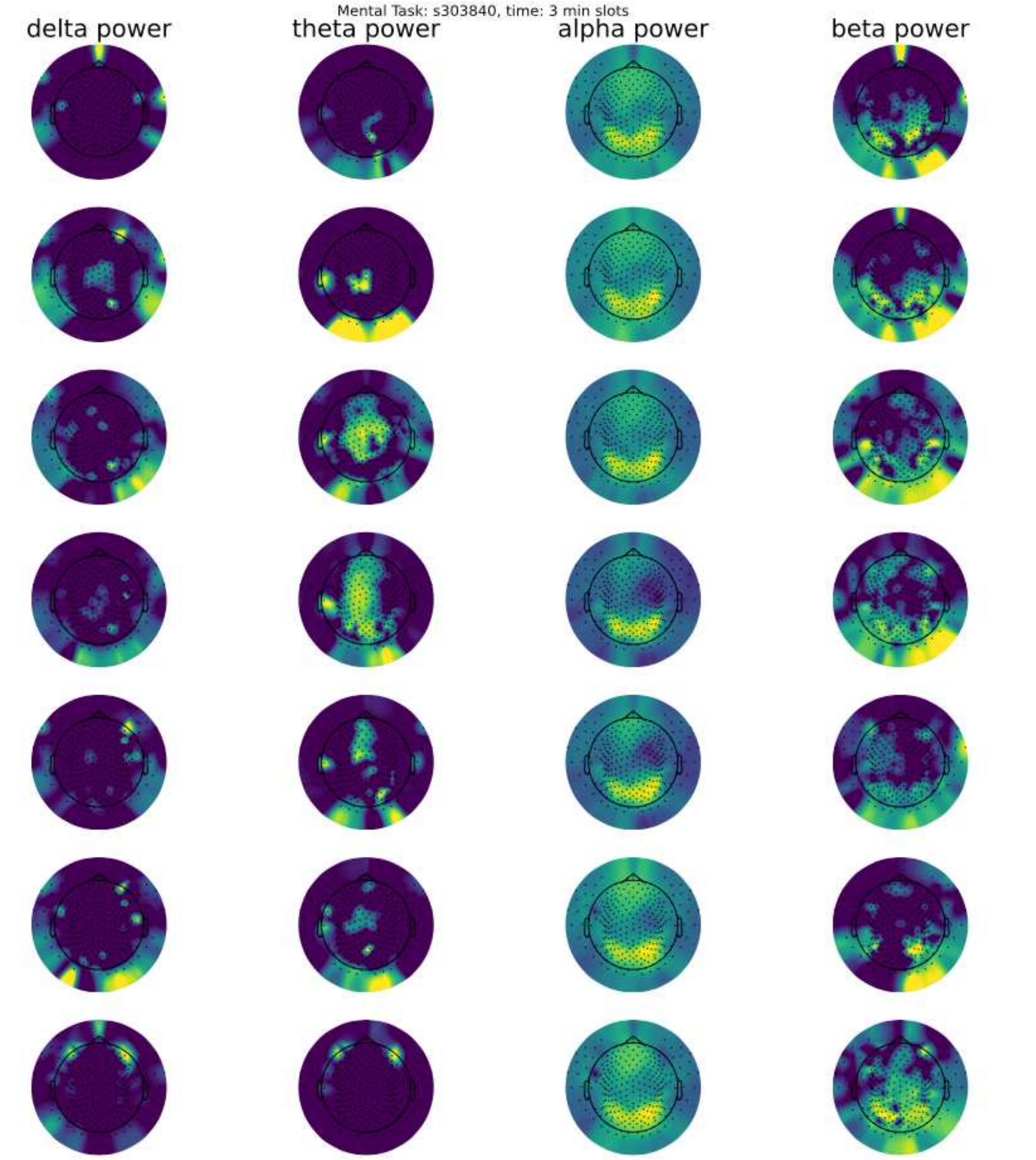

Figure 3. Power activity in the δ, θ, α, and β bands for participant s303840 exposed to mental task. Each row, one-by-one, represents a 3-min slot, for 21-min in total. For details, see the text.

The training and validating sets were divided into proportions of 80% and 20%, respectively.

Table 1 shows the results of the GLM classifier for Group A. The 3 s long time intervals were investigated around the 5th, 10th, 13th, 14th, and 15th minutes. The choice of these probing times was arbitrary based on the experience of the GI relaxation therapist.

The results of the GLM classifier for Group B are shown in Table 2, where a 60 s time interval was chosen because we suspected that the signals were of worse quality in this group. The probing was investigated around the 5th, 10th, 13th, 14th, and 15th minutes and the following 1 min after each probe.

Table 3 shows the results of the GLM classifier for Group B, and the whole 20-min signal recordings were classified without any signal probing.

In Figure 4, the ROC curve for the GLM applied to Group B using the full-length 20-min signal recordings is presented. The set of statistical characteristics for this case are presented as follows: For the training set: MSE: 0.0634, RMSE: 0.2518, LogLoss: 0.2021, AUC: 0.9748, AUCPR: 0.9834; For validation set: MSE: 0.05227, RMSE: 0.2286, LogLoss: 0.1676, AUC: 0.9823, and AUCPR: 0.9877.

Table 1. GLM classifier results for Group A: all signals and 3 s time intervals.

Group	dT (s)	ACC Train	F1 Train	AUC Train	ACC Valid	F1 Valid	AUC Valid
A	299–301	0.6559	0.7165	0.7255	0.6252	0.7027	0.6808
A	599–601	0.6578	0.7156	0.7291	0.6401	0.7051	0.7006
A	779–781	0.6853	0.7326	0.7672	0.6693	0.7279	0.7451
A	839–841	0.6842	0.7336	0.7663	0.6629	0.7221	0.7355
A	899–901	0.6660	0.7177	0.7441	0.6506	0.7167	0.7252

Table 2. GLM classifier results for Group B: all signals and 60 s time intervals.

Group	dT (s)	ACC Train	F1 Train	AUC Train	ACC Valid	F1 Valid	AUC Valid
B	299–359	0.7785	0.8337	0.8620	0.7804	0.8360	0.8602
B	599–659	0.7884	0.8407	0.8678	0.7955	0.8478	0.8727
B	779–839	0.8097	0.8532	0.8926	0.8113	0.8578	0.8929
B	839–899	0.7830	0.8367	0.8628	0.7827	0.8409	0.8631
B	899–959	0.7812	0.8345	0.8634	0.7839	0.8410	0.8625

Table 3. GLM classifier results for Group B: all signals and full signal length.

Group	dT (s)	ACC Train	F1 Train	AUC Train	ACC Valid	F1 Valid	AUC Valid
B	1–1200	0.9258	0.9370	0.9822	0.9077	0.9238	0.9748

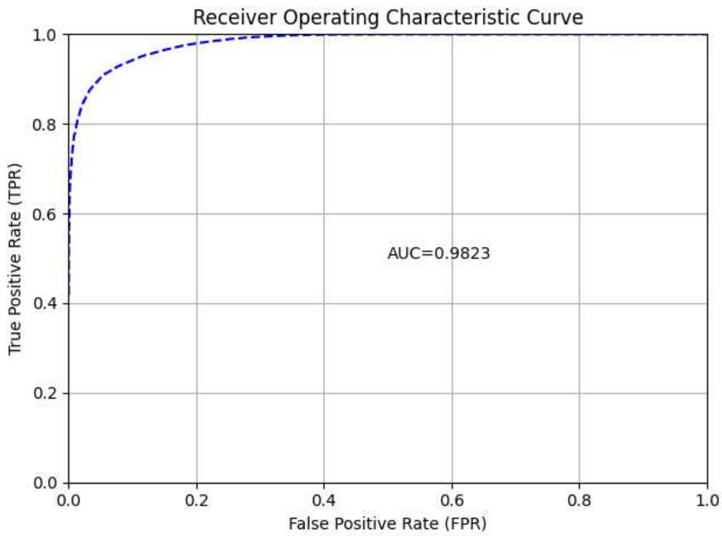

Figure 4. The ROC curve for the results presented in Table 3.

Table 1 shows that the best results, with approximately 68% accuracy, were achieved near the 13th and 14th minutes using the GLM classifier. A 3 s time interval was sufficient for analyzing and estimating the state of the brain during the time in which it was recorded.

Figures 5 and 6 show topographical maps of participants from Figures 2 and 3 for five frequency bands of the time window where the classifier was performing best.

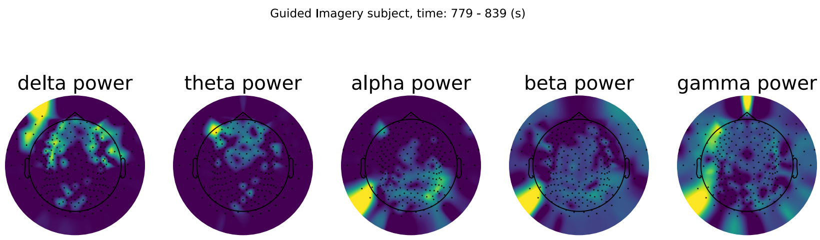

Figure 5. Power activity in the δ, θ, α, and β bands for participant s299392 exposed to guided imagery.

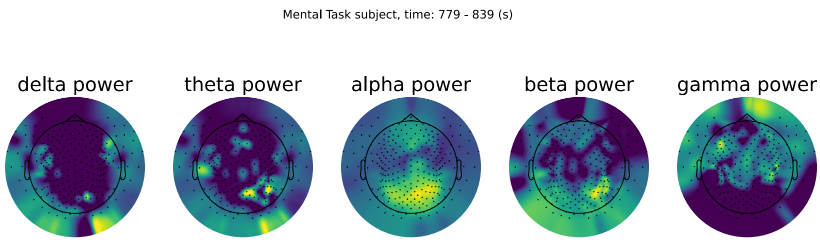

Figure 6. Power activity in the δ, θ, α, and β bands for participant s303840 exposed to the mental task.

4. Discussion

4.1. Signal Classification

According to our experience and expectations, most of the patients were sufficiently relaxed in the 14th minute. The best results of the classifier at this time confirmed our expectations, to some extent. To examine the hypotheses about the substantial increase in alpha power and decrease in beta (to some extent) power in the estimated phase of deepest relaxation, we carried out the two one-way ANOVAs comparing the individual scores in brainwaves between group conditions (guided imagery or mental task) during the time phase of 14 min. We found predicted, significant effect of group (F (1, 53) = 4.01, p = 0.05, p2 = 0.070), indicating that the alpha power in the guided imagery group (M = 0.24, SD = 0.14) was significantly higher than that in the mental task group (M = 0.17, SD = 0.12). However, we found no significant effect of group for beta power scores (F (1, 53) = 0.53, p = 0.47, p2 = 0.010), and beta power in the guided imagery group (M = 0.08, SD = 0.03) was very similar to that in the mental task group (M = 0.07, SD = 0.03). However, only the best signal (with less than 10% excluded epochs) was considered. Table 1 presents the GLM results obtained for both the training set and validation set, and the values of the obtained parameters confirmed the classifier's high level of stability in the considered time range.

As an accuracy of 68% was achieved by the classifier when using a 3 s time interval, we wondered if inputting more signal would increase the efficiency. The answer to this was yes, and in Table 2, the results with respect to classifier efficiency for 1-min-long intervals of time are shown. After 13 min, the efficiency of the GLM increased to 78%, which is a satisfactory result, especially because, in this case, we took all the signals recorded instead of the best ones. Notably, poor epochs were interpolated by the software and used for analysis, as described in the Methods section. Similarly, Table 2 presents the GLM results obtained on both the training and validation sets, and the values of the obtained parameters indicate the classifier's high level of stability in the discussed time range.

Table 3 presents the results obtained for the GLM classifier for all collected signals in the whole 20-min-long time range. An accuracy of approximately 92% with a similar F1 score proved its high efficiency for the whole collection of data, both on the training and validation sets. Th ROC curve presented in Figure 4 confirms its stability.

The software libraries discussed in the Methods section provided us with overtraining and data leakage incidents.

The aim of this study was to check whether machine learning can be used to classify the state of the participant's brain and distinguish engaging in deep GI relaxation from performing a mental task. The results presented herein confirm this possibility.

The other conclusion that can be derived from this study is that the more signal (or the longer signal) the classifier obtains, the higher the accuracy.

4.2. Future Research

This study is part of the initial stage of our project.

Depending on personal characteristics and external influence, each patient has their own ability to enter into relaxation, which varies with respect to time and other conditions.

In the future, the pace at which particular subjects enter a deep state of relaxation. should be investigated. We expected that this could be achieved in approximately 14 min. However, each individual can be characterized by their own pace. Plotting the state as a function of time would be recommended.

The use of machine learning classifiers is expected to be applied in the classification of biomedical signals at therapy support sites [51,52]. Machine learning tools and algorithms have also been used for decades for the diagnosis of many disorders, such as alcoholism or depression [53,54], among others [55], using new measures such as those defined in [56], as well as advanced modeling of biological system behavior [57–60], including diagnostic purposes [61–63].

Our findings are useful for the construction of brain–computer interfaces (BCIs) that have been known for half a century [64,65] and can support therapists in running GI relaxation sessions. In the next step, we can imagine AI-trained robotic therapists that are able to instantaneously treat their patients at an appropriate pace based on EEG recordings and classifiers applied. Although BCIs have been known for such a long time, some ethical dilemmas may arise when using them [66], especially with children [67]. Thus, another interesting aspect is the investigation of the characteristics of the deep state of relaxation inclination as a function of psychological personality predictors.

In the future, patients provided with simple EEG equipment will be able to use it during relaxation to support a trainee during brain monitoring. This type of approach could increase the effectiveness of therapy, and the study presented here can be the first step toward achieving this goal.

Another aspect leading to the possible application of this finding, especially when considering therapist support, is the design of tools that can be used to instantaneously process the collected data. Although the use of 256 electrodes can be too power-consuming, in practical applications, fewer electrodes may be sufficient. The data analysis pipeline may also consist of an Apache Spark Streaming-based engine, such as in [68], which, due to in-memory processing and the Python interface, seems to be a suitable candidate for pipeline implementation.

This will, however, require the analysis of several additional tests. After meditation vs. control manipulation, we examined the effectiveness of attentional processes (accuracy and reaction time) using three classical tests: the antisaccade test, Stroop test, and go/no-go test. They did not affect the EEG recordings, but their analysis was not the goal of this study. This type of approach will broaden our knowledge concerning relaxation interventions and will be reported in future papers.

Author Contributions: K.Z.: meaningful participation in the key phases of research and publication process, research project conceptualization, verification of results and analysis, manuscript writing, responses to reviewers, literature review, and implementing guided imagery relaxation technique; G.M.W.: head of the project, experiment idea and coordination, data science pipeline design, and manuscript writing; K.W.: EEG recordings, work in the laboratory, and data analysis; F.P.: EEG recordings, work in the laboratory, and data analysis; A.K.: classifier construction advise and evaluation; G.S.: research idea, selection of participants to the cohort, and statistical analysis. All authors have read and agreed to the published version of the manuscript.

Funding: Research presented herein was supported by the City of Lublin as a part of cooperation of Lublin City Hall and Maria Curie-Sklodowska Univeristy towards pilot study for VRMed project.

Informed Consent Statement: The studies involving human participants were reviewed and approved by the Maria Curie-Sklodowska University Bioethical Commission (MCSU Bioethical Commission permission 9 July 2021). The patients/participants provided their written informed consent to participate in this study. Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The raw data supporting the conclusions of this manuscript will be made available by the authors without undue reservation to any qualified researcher.

Acknowledgments: The authors would like to thank Ewa Lewandowska and Marek Rudziński of VRMed for fruitful discussions, inspiration and possibility of working together on new ideas.

Conflicts of Interest: The authors declare no conflict of interest.

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6.3 Investigating the Impact of Guided Imagery on Stress, Brain Functions, and Attention: A Randomized Trial

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Special Issue
Biomedical Data in Human-Machine Interaction

Edited by
Prof. Dr. Aleksandra Kawala-Sterniuk, Prof. Dr. Grzegorz Marcin Wójcik and Dr. Waldemar Bauer

MDPI

https://doi.org/10.3390/s23136210

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Investigating the Impact of Guided Imagery on Stress, Brain Functions, and Attention: A Randomized Trial

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Abstract: The aim of this study was to investigate the potential impact of guided imagery (GI) on attentional control and cognitive performance and to explore the relationship between guided imagery, stress reduction, alpha brainwave activity, and attentional control using common cognitive performance tests. Executive function was assessed through the use of attentional control tests, including the anti-saccade, Stroop, and Go/No-go tasks. Participants underwent a guided imagery session while their brainwave activity was measured, followed by attentional control tests. The study's outcomes provide fresh insights into the influence of guided imagery on brain wave activity, particularly in terms of attentional control. The findings suggest that guided imagery has the potential to enhance attentional control by augmenting the alpha power and reducing stress levels. Given the limited existing research on the specific impact of guided imagery on attention control, the study's findings carry notable significance.

Keywords: guided imagery; relaxation; stress reduction; cognitive performance; EEG; GLM

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Citation: Zemla, K.; Sedek, G.; Wróbel, K.; Postepski, F.; Wojcik, G.M. Investigating the Impact of Guided Imagery on Stress, Brain Functions, and Attention: A Randomized Trial. *Sensors* **2023**, *23*, 6210. https://doi.org/10.3390/s23136210

Academic Editor: Yvonne Tran

Received: 5 June 2023
Revised: 28 June 2023
Accepted: 4 July 2023
Published: 7 July 2023

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1. Exploring the Impact of Relaxation Techniques on Brain Wave Activity and Attentional Performance: A Review of Relevant Research

Improving attention and executive functions is of great importance in our current world due to the complex and demanding nature of daily tasks and the challenges posed by our modern reality. Scientific research has shown that attention and executive functions play crucial roles in various aspects of cognitive processing and goal-directed behavior [1]. Attention is the cognitive process that allows us to selectively focus on relevant information while filtering out irrelevant stimuli [2]. It is essential for tasks that require concentration, information processing, and decision making. In our information-rich environment, where we are constantly bombarded with stimuli and distractions, the ability to maintain focused attention is vital for productivity and task performance. Scientific studies have consistently demonstrated the positive impact of enhanced attention and executive function on various aspects of individuals' lives [3]. Improved attentional control and executive function have been associated with a better academic performance [4–6] and job performance [7] and professional success. Additionally, they contribute to effective decision making, problem solving, and conflict resolution. Hence, improving attention and executive functions is vital in our current world, given the cognitive demands and challenges we face, ultimately benefiting individuals and society as a whole in wide range of EEG experiments designed to quantitatively measure cognitive functions like those in [8]. In recent years, there has been a growing interest in studying the effects of meditation and relaxation techniques on attentional control processes. Tang [9] conducted a study that demonstrated how just five days of mindfulness meditation training improved attentional control in healthy young adults. Similarly, Zeidan [10] found that brief mindfulness meditation training improved executive attentional control abilities and reduced anxiety. Furthermore, Ruedy and Schweitzer [11] found that a brief period of relaxation exercises enhanced participants' ability to resist distractions and maintain focus on a cognitive task. Several reviews have also analyzed the impact of meditation on cognitive functions, including attention, memory, and executive control. For instance, Chiesa and Serretti [12] examined the effects of mindfulness meditation on attentional control and found that it led to improvements in both selective and sustained attention. Many studies in cognitive psychology and neuroscience have explored the positive impact of mindfulness and meditation training on cognitive functions. These studies have utilized a wide range of tasks to assess measures of response accuracy, response time, and associated electrophysiological and neuroimaging patterns, highlighting the positive impact of mindfulness and meditation on cognitive performance [9,13–17].

Despite being recognized as a healing resource for centuries [18], the potential impact of guided imagery (GI) on cognitive performance remains largely unexplored. In recent years, there has been increased interest in the role of GI in health and well-being [19]. GI has also been found to be effective in enhancing sports performance [20]. In the late 1970s, health professionals reported using imagery for altering the course of life-threatening diseases [21,22]. Studies have shown that GI can reduce psychological stress and smoking behaviors among smokers and ex-smokers [23], and can facilitate improved health behaviors and reduce psychological distress in the workplace [23]. GI involves external instructional guidance to allow the internal generation of images [24], and it is defined as the mental process that employs the senses of sight, hearing, smell, and taste. Sensations of motion, position, and contact are experienced by GI practitioners [25]. GI has wide-ranging relevance and applicability, and is effective in reducing test anxiety [26], coping with stress [27–35], and improving problem-solving abilities [36].

Given the evidence of both anxiety reductions and immune system enhancements, GI has not been studied during brain behavior and brainwave changes while patients are conducting GI sessions. However, the ever-growing neuroscience literature relating to the phenomena of mindfulness sessions is trying to incorporate EEG quantitative measurements to describe brain wave changes during mindfulness sessions [37]. For example, in the research led by Peta Stapleton, the brainwave data of a group of 468 meditation novices with limited previous exposure to forms of guided meditation were recorded, and researchers observed a global increase of 16% (95% HDI = [0.13, 0.19]) in alpha power due to meditation [38]. A range of mindfulness-based techniques has been created to reduce stress and enhance the quality of life [39]. Meditation is a complex conscious cognitive process requiring concentration and receptive attention [9,40]. Meditation practices are also associated with enhanced executive function and working memory [41–45]. However, little research has provided an electrophysiological examination of the meditative experience in people with limited meditation experience, particularly from a GI perspective. However, it is known that alpha activity in EEG signals during meditation is a form of brain integration that leads to higher-level cognitive processes [46]. Researchers hypothesized that the transition from beta brainwaves (high, medium, and low range) to alpha brainwaves could take place relatively quickly [38]. This result is consistent with the findings of a study in which participants achieved proficiency in the attentional training aspect of meditation practice relatively swiftly [47]. An increase in alpha wave levels indicates that the participants are in a relaxed mood or their mood is enhanced [48]. Under stress, the alpha brain waves tend to decrease, which can indicate a state of heightened arousal and anxiety. The alpha frequency is also positively correlated with the speed of processing information [49]. On the other hand, the beta wave power indicates that humans are in an alert condition [50]. An increased beta activity can interfere with the ability to relax and can make it difficult to focus attention on a single task. Research has shown that stress can interfere with attention control by reducing our ability to filter out distractions and interfering with our ability to shift our focus from one task to another [51]. Zoefel proved [52] that an increase in EEG alpha wave activity is linked to an improvement in cognitive performance. Cognitive control (CC) and executive function (EF) are defined in relation to goal-directed behavior versus habits and controlled versus autonomic processing, as well as the functions of the prefrontal cortex (PFC) and associated regions and networks [53]. Executive functions (EFs) consist of a family of three, interrelated core skills: (1) inhibition or active suppression of stimuli and automatic responses that are irrelevant to the task at hand, (2) updating and monitoring of information in the working memory to include only the most relevant material, and (3) shifting or switching attention between multiple mental representations or operations [54].

Anti-saccade, Stroop, and Go/no-go tasks are three commonly used tests to assess executive function, which refers to a set of cognitive processes involved in goal-directed behaviors [55]. These tasks have been extensively studied and validated, allowing for meaningful comparisons across different studies and populations [56]. Although all three tests are measures of executive function, they differ in their specific cognitive demands and the underlying processes they assess. Anti-saccade tasks assess inhibitory control and attentional control [54,57], Stroop tasks assess selective attention and inhibition of irrelevant information, and Go/No-go tasks assess response inhibition and working memory [58]. It was proven that acute psychosocial stress may affect executive action control in a Go/No-go task [51].

No research was found on attentional tasks after GI sessions. However, it is known that other relaxation techniques such as meditation can reduce interference during the Stroop task [59], and meditators have better attentional performance in the Stroop task compared with a meditation-naïve control group [60]. High proficiency in this task indicates good attentional control and relatively low automaticity or impulsivity of one's responses [13]. The study titled "Mindfulness-of-breathing exercise and its effect on EEG alpha activity during cognitive performance in an attentional Stroop task" investigates the relationship between a mindfulness-of-breathing exercise and EEG alpha activity during cognitive performance, specifically in the context of an attentional Stroop task [61]. The study results showed a significant increase in alpha power during the intervention among the mindfulness-of-breathing exercise group compared to the control group. The mindfulness-of-breathing exercise group also demonstrated a trend toward enhanced performance in the Stroop attentional blink task after the intervention. The authors suggest that the increased alpha power may potentially facilitate cognitive performance [61]. Another study "Short Term Integrative Meditation Improves Resting Alpha Activity and Stroop Performance" [62] provides evidence that a short-term integrative meditation program can improve the resting alpha activity and cognitive performance in the Stroop task. Another commonly used measure of cognitive inhibition is the anti-saccade (AS) task, which requires suppression of a visually guided saccade toward a target and the generation of voluntary saccades in the opposite direction. In was concluded in [57,63] that more accurate and more consistent AS performances were present in meditators in comparison to the non-meditators group. Go/No-go tasks can provide objective evidence of attention lapses in the form of target omission errors and response time variability. In [64], the authors reported that mindfulness is related to errors on Go/No-go tasks with high self-reported mindfulness scores are related to more accurate responses [60,65–68]. Inhibition, shifting, and updating are core abilities that support a mindful state and are facilitated via regular meditation [69]. For example, inhibition of unrelated mental representations and reactions is required to maintain a mindful state, with inhibitory control increasing once a mindful state is achieved via implicational intentions (e.g., if the mind is wandering, then disengage and refocus attention). Shifting is necessary to mentally clear distractions and unrelated representations back to the present-moment experience. Finally, updating the working memory is required to continually stay focused on an ever-changing present moment [70].

However, there is no research on GI and its impact on the results of attention tests. Only [71,72] verified and proved that relaxation induced by GI significantly enhanced working memory performance, but there is no other research on the topic that this research investigates.

2. The Potential Benefits of Guided Imagery for Executive Function and Attentional Control and Research Hypotheses

Guided imagery offers a distinct experiential approach to mindfulness and mental well-being. Although meditation primarily focuses on cultivating present-moment awareness and detachment from thoughts, guided imagery involves actively engaging the imagination to create vivid sensory experiences. This approach can be particularly helpful for individuals who find it challenging to quieten the mind or those who benefit from more structured practices. A further exploration of guided imagery is interesting as it broadens our understanding of mindfulness, offers customization, and provides a complementary practice to enhance mental health.

Overall, mindful meditation and GI practices can be effective for improving attention control and cognitive performance; however, the specific benefits and mechanisms of action differ depending on the practice. Mindfulness meditation develops greater awareness and control over the mind [73] and GI promotes positive emotions and reduces stress and anxiety, whereas anxiety impairs the cognitive performance by increasing cognitive interference [74]. Effective stress management strategies, such as relaxation techniques, may be helpful in mitigating the negative effects of stress on attention and cognitive functions. Attentional control theory posits that for goal-directed behavior to occur, attentional control is necessary, involving inhibiting competing demands to concentrate on the current task and being able to switch or shift attention as necessary [75]. Attentional control theory specifies that deficits in these aspects of attentional control are central to the development and maintenance of anxiety [75]. In support of this assumption, a recent meta-analysis of 58 studies testing the association between measures of attentional control and anxiety found that participants with high anxiety showed a deficit in attentional control compared to participants with low anxiety [76].

The main research hypothesis of this study was that a short-term GI session would reduce stress levels in healthy male participants without prior experience with such sessions or a history of chronic medical conditions. To test this hypothesis, 30 participants were randomly selected to undergo a GI session, and the effectiveness of the session in reducing stress was assessed through monitoring beta power reductions and alpha state increases using EEG data recordings and self-reported questionnaires.

In addition to evaluating the effectiveness of the GI session, this study aimed to investigate whether the results of attentional tasks (Stroop, Go/No-go, and anti-saccades tests) could differentiate between the group of participants who underwent the GI session and another group of 30 randomly selected male participants who completed a mental task. Specifically, the number of errors made on these tasks between the two groups was compared.

Furthermore, the study hypothesized that changes in alpha power might mediate the relationship between the utilization of GI and the decrease in errors on the Stroop and anti-saccade tests. To test this hypothesis, a mediation analysis was conducted to explore the possible relationship between these variables.

3. Materials and Methods

3.1. Materials

Before the experiment, the participants were required to sign a consent form confirming their willingness to participate. The participants were also required to fill in their personal information and answer several questionnaires as outlined below:

1. Scales of Helplessness and Anxiety of Contracting an Infectious Disease by Rydzewska, K. and Sędek, G. 2020 unpublished research materials from SWPS University of Social Sciences and Humanities. These measures were used to indicate the potential role of high levels of maladaptive emotions in impeding rational decision making during the pandemic.
2. The State-Trait Anxiety Inventory (STAI) is a self-reporting questionnaire designed to measure anxiety in adults. The STAI questionnaire is often used in medical and

research settings to help identify people who may need treatment for anxiety [77]. It can also help to measure the effectiveness of treatments designed to reduce anxiety.

3. Following both the GI and mental task sessions, participants underwent attentional tests to test the hypothesis that GI can enhance attentional control.
   The anti-saccade test—attention control was designed according to the recommendations of the Antoniades protocol. In prosaccade trials, the object appears at the location of the cue, so the discrimination of stimuli is relatively easy. The primary indicator in this task is the average percentage of correct responses for the anti-saccade blocks.
   The numerical Stroop Test is a variation of the classic Stroop test that uses numbers instead of words. The test is designed to create interference between the automatic response of reading the digits and the task of counting them, which requires more cognitive effort. The test measures the ability to suppress automatic responses (response inhibition) and focus attention on the task at hand [78].
   The main indicator in this test is the average percentage of correct answers.
   Go/no-go tasks require participants to respond to one type of stimulus (the "go" stimulus) but inhibit their response to another type of stimulus (the "no-go" stimulus). This task assesses the ability to inhibit automatic responses and cognitive flexibility, as well as response inhibition and working memory [58]. The tasks in the main block were arranged in a pseudorandomized order while following the rule that No-go trials were preceded by two or five Go trials. The main block of trials was preceded by ten practice trials, consisting of two No-go and eight Go trials. As a primary measure of Go/No-go task performance, the attention control was the percentage of correct responses to Go trials after No-go trials.
4. Furthermore, both prior to and following the GI and mental task sessions, the study participants were given questionnaires developed by the research team. These questionnaires encompassed various measures, including participants' self-reported levels of stress and relaxation on a 10-point scale, and enabled the identification of emotions experienced by the participants before and after the GI and mental tasks.

The experimental group underwent a recorded GI session, in which participants were provided with a series of instructions to visualize a calming and peaceful scenario. The session began with simple breathing exercises and progressive muscle relaxation techniques. The mental task group listened to a pre-recorded session consisting of mental tasks that involved recalling the names of voivodeships in Poland, zodiac signs, and other similar tasks. The inclusion of a mental task in the second group, rather than a resting state condition, was designed to simulate the experience of stress. Stress is known to elicit negative thoughts and worry, leading to cognitive rumination [79]. This repetitive thinking about stressors, problems, or potential threats can be mentally exhausting and hinders the ability to achieve a state of relaxation. The cognitive load associated with stress-related thoughts keeps the mind engaged, making it difficult to enter a restful state. Therefore, the use of a mental task was aimed to replicate the cognitive demands and stress-related cognitive processes often experienced in real-life stressful situations.

Both experimental groups, including the guided imagery group and the mental task group, were subjected to identical conditions, which involved listening to pre-recorded instructions for the same duration. Furthermore, each experimental session was supervised by two trained technicians who diligently attended to technical aspects, ensuring proper electrode placement and functioning, including the playback of the recordings.

To determine whether participants in the guided imagery and mental task group were actively engaged in the experiment and not sleeping, researchers employed several strategies to minimize the likelihood of participants falling asleep during the session summarized in the following. Monitoring: Researchers were present during the session and monitored participants during the guided imagery session and mental task session. This allowed to visually confirm whether participants remained awake and actively participated throughout the session. Instructions: Clear instructions were provided to participants before the guided imagery session and mental tasks session, emphasizing the importance of staying awake and engaged. Post-session debriefing: After the guided imagery session and mental task session, researchers conducted a debriefing via a survey with participants to ask about their experience and level of engagement. These measures, combined with the researchers' direct observations and vigilance, can provide valuable evidence to ascertain whether participants in the guided imagery group remained awake and actively participated in the experiment. However, it is important to note that despite these efforts, it is challenging to completely eliminate the possibility of some participants unintentionally falling asleep during a session. However, the study conducted by Yaxin Fan "Short Term Integrative Meditation Improves Resting Alpha Activity and Stroop Performance" [62] provides evidence that, in contrast to the significant changes observed in the meditation training group, no significant alterations in alpha power or performance on attention tasks are observed even during a resting state in the control group.

3.2. Experimental Facilities

The EEG Laboratory located within the Department of Neuroinformatics and Biomedical Engineering is equipped with a dense array amplifier that can capture brain electrical activity at a frequency of 500 Hz using a 256-channel HydroCel GSN 130 Geodesic Sensor Net. This complete and compatible system is manufactured by Electrical Geodesic Systems, and it utilizes a Geodesic Photogrammetry System (GPS), which uses 11 cameras placed in its corners to create a model of the subject's brain based on its size, proportion, and shape. This system is able to accurately superimpose computed activity results onto the brain model. The amplifier works in conjunction with the Net Station 4.5.4 software, while the GPS is controlled by Net Local 1.00.00 and GeoSource 2.0. Eye tracking was achieved through the use of a SmartEye 5.9.7 system, which allows for gaze calibration and the elimination of eye blinks and saccades. PST e-Prime 2.0.8.90 was used to design the ERP experiments.

3.3. The Cohort

The Bioethical Commission of Maria Curie-Sklodowska University in Lublin, Poland, granted permission for all the experiments described below. During the relaxation experiment, each participant in the cohort sat in a comfortable armchair with earphones and listened to a recording of a relaxation procedure. The recording was prepared by a trained expert using a typical method of GI, which as explained above in detail is a relaxation technique that involves focusing on a positive mental image or scene. The recording was 21 min and 7 s long, but for this research, only the first 20 min were considered. It was assumed that each member of the sub-cohort would eventually become relaxed enough to manifest brain cortical activity that could be classified.

We utilized our dense array amplifier to capture the signals across all 256 electrodes. However, considering our prior expertise [80–82] in analyzing cognitive processing EEG signals, we anticipated detecting variations specifically ion the designated cognitive electrodes. These electrodes are designated as optimal for observing cognitive activity according to the EGI 256-channel cap specifications. They were strategically positioned across the scalp, and they are sequentially numbered as follows: E98, E99, E100, E101, E108, E109, E110, E116, E117, E118, E119, E124, E125, E126, E127, E128, E129, E137, E138, E139, E140, E141, E149, E150, E151, and E152. The topographical map of these electrodes as places on the scalp can be found in Figure 1 in the EGI documentation [83,84].

The research protocol for both types of sessions is presented in Figure 1.

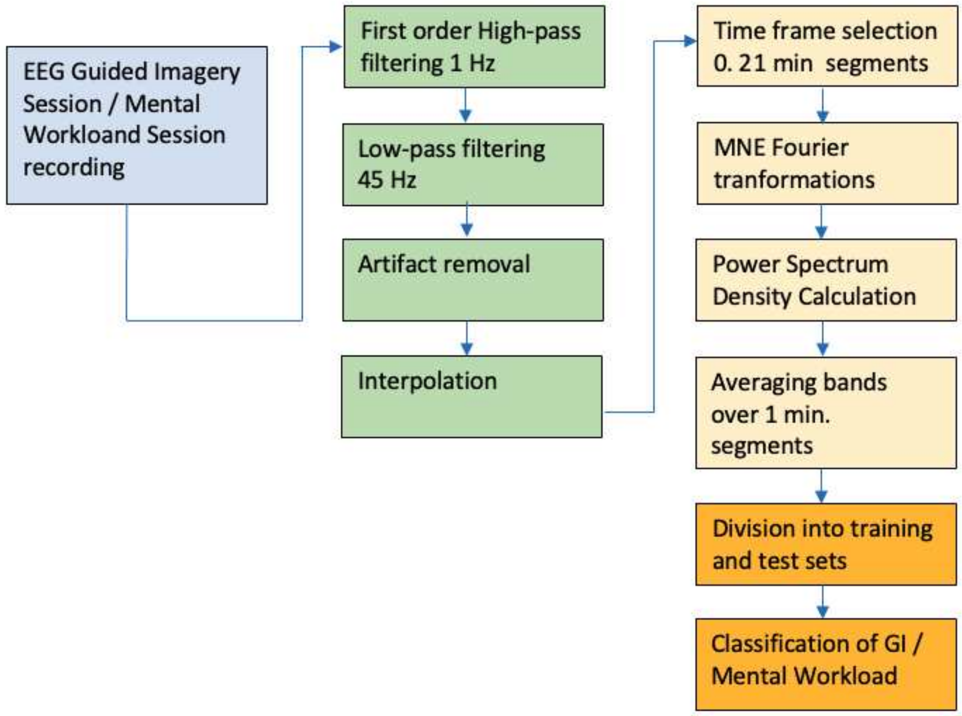

Figure 1. Research protocol used for data processing of both types of sessions: GI and mental task workloads.

After the signal was recorded, we exposed it to low and high pass filtering, removed artefacts, and continued with the so-called interpolation of electrodes. Next, the signal was divided into 1 min long segments and Fourier transforms were applied to the calculation of the power spectrum densities (PSDs) to be averaged over this 1 min long time interval. Next, the data were divided into training and testing sets (80%/20%) and the classifier worked on the signals that it has never seen before.

During the mental task experiment, participants were asked to recall as many European country capitals, zodiac signs, and United States states from memory as possible. They were told that they would be asked to write down their responses after the experiment and that their reward depended on the results. It was assumed that this task would require mental effort, leading to a high level of mental workload and a stressful situation.

Initially, 60 participants were recruited from the students of Computer Science at Maria Curie-Sklodowska University in Lublin. These were all right-handed males aged 17 to 24, with an average age of 20.38 and a standard deviation of 1.52. Only men were chosen for the experiment because mainly male students of Computer Science attend the University where the research was conducted, and differences in electroencephalograms between men and women have been reported [85,86]. This was done to achieve a relatively equal cohort response.

It was ensured that the participants did not suffer from chronic diseases. They were asked to declare any serious diseases such as chronic fatigue syndrome, cancer, and other chronic diseases, including mental disorders, and if they did, they were automatically excluded from the cohort. The experimental cohort was divided into two sub-cohorts: A consisted of 30 subjects exposed to relaxation, and B consisted of 30 subjects asked to perform the mental task.

3.4. Inclusion and Exclusion Criteria

The inclusion criteria for the cohort in this experiment include being a short-haired, right-handed, healthy, Polish-speaking male between the ages of 17 and 24, with no history of chronic diseases, no current use of prescribed medication, soft drugs, or hard drugs, and the ability to attend study appointments with no technological requirements. Participants were also asked not to consume alcohol or any medication at least 72 h before participation in the experiment.

Exclusion criteria included being younger than 17 or older than 24 years, being left-handed, having long hair, not fluently speaking the Polish language, being seriously or chronically ill, currently taking prescribed medication, soft drugs, or hard drugs, having a medical treatment history in one year following the study, or being unable to attend study appointments. Participants who did not meet the inclusion criteria or declared any serious diseases, including mental disorders, were automatically excluded from the cohort. Prior to participating in the experiment, participants received information about EEG research and technology and signed an agreement for participation.

The proportion of women pursuing a computer science education remains low, making it challenging to create a well-balanced group for the experiment that included an equal number of left-handed and right-handed men and women. Additionally, it was observed that a significant majority of women studying computer science had long hair. It is worth mentioning that studies have documented variances in electroencephalogram readings between men and women [85,86], and we aimed to ensure a relatively equal response from the cohort.

3.5. The 14th min Choice Justification

In summary, the choice of the 14th min for analysis was based on a previous postulation that it is the most likely time for the participants to be experiencing a deep state of relaxation. To confirm this, the generalized linear model classifier (GLM) was used to distinguish between relaxation and mental state with an approximately 80% accuracy.

The generalized linear model enhances the general linear model by introducing a specified link function to establish a linear association between the dependent variable and the factors and covariates. The advantage over the general linear model is that there is no need for the data distribution to be normal. In the case of the presented research, the link function was logit. The dependent variable was the Mental Workload or Guided Imagery group. The factors were band (alpha, beta, and theta) powers from every minute of the recordings.

Generalized linear models (GLMs) are often used for time series analyses [87] and it is not aim of this paper to explain in detail all its cases and formulas. However, the idea of GLM consists of three components:

1. An exponential family of probability distribution (this means it is not necessary for a normal distribution);
2. A linear predictor $\eta = X\beta$;
3. A link function g such that $E(Y) = \mu = g^{-1}(\eta)$

where Y is the dependent variables vector (in our case GI/Mental task workload), E(Y) is the expected value of Y (it is either GI or MT), g is the so-called linking function (in our case *logit*), X is a matrix of the independent variables (in our case values collected from the EEG bands), and β represents model factors and is set by the model while training. In our case, the model is expressed by:

$$g(E(Y)) = X\beta \tag{1}$$

and g is a function expressed by:

$$logit(p) = \sigma^{-1}(p) = ln\frac{p}{1-p} \tag{2}$$

for $p \in (0,1)$.

To further validate the choice of the 14th min, the GLM accuracy was tested on each one-minute-long interval of time, from the beginning to the end of the recordings. The results showed a local maximum in the 14th min for both GI and Mental task sessions, followed by a falling slope until the 16th min. After the 17th min, the waking up process started, and the classifier's accuracy increased, indicating a different and distinguishable state of brain activity. Therefore, the 14th min was chosen as the appropriate time for further analysis (Figure 2).

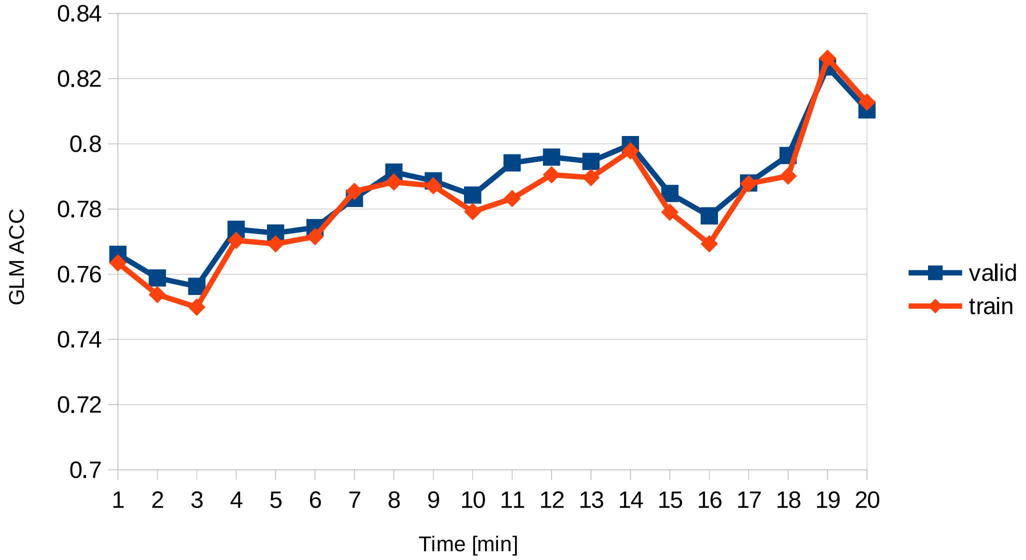

Figure 2. The 14th min choice justification.

The intention behind using machine learning classifiers was to help in the classification of biomedical signals for therapy support [88,89]. These tools and algorithms have been used for a long time for the diagnosis of various disorders, such as alcoholism or depression [90,91]. Additionally, they have been used to measure various biological system behaviors and for diagnostic purposes [92]. Advanced modeling techniques have also been employed to better understand these systems [93,94]. The use of new measures, such as those defined in recent research [95,96], has further advanced the accuracy of these models.

3.6. The Final Cohort

Finally, after pre-processing the signal and eliminating the poor quality, as well as leaving only the participants who provided as with a full set of data and good EEG recordings and taking into account all the exclusion criteria, we had 20 subjects left in the GI sub-cohort and 28 subjects in the mental task engaged sub-cohort.

4. Statistical Analysis of the Data

The current study aimed to compare the effects of GI and a mental task intervention on cognitive and emotional measures, as well as to explore potential correlations between these measures. A group of participants were randomly assigned to either the GI or mental task group and completed a series of tests, including brain wave measures, attentional control tasks, and anxiety and affective measures.

Table 1 shows the participants' characteristics for subjective measures in a study with two groups: the GI group (N = 20) and the mental task group (N = 28). The measures include anxiety, helplessness, stress reduction, and relaxation increase. A one-way analysis of variance (ANOVA) was conducted to test for significant differences between the groups.

In neuroscience research, longitudinal data are often analyzed using an analysis of variance (ANOVA) and a multivariate analysis of variance (MANOVA) for repeated measures (rmANOVA/rmMANOVA) [97]. MANOVA is an extension of ANOVA, which measures the impact of independent categorical variables upon numerous dependent continuous variables. It is a process used for comparing the sample means, which are multivariate in statistics. MANOVA is mostly used in a population with more than two variables. It is a non-parametric test. However, these analyses have special requirements:

The variances of the differences between all possible pairs of within-subject conditions (i.e., levels of the independent variable) must be equal. They are also limited to fixed repeated time intervals and are sensitive to missing data [97]. In contrast, other models such as the generalized estimating equations (GEE) suggest another way to consider the data and the studied phenomenon. Instead of forcing the data into the ANOVAs assumptions, it is possible to design a flexible/personalized model according to the nature of the dependent variable.

We decided to use an ANOVA for our data analysis due to its balance and neuroscientific character.

Table 1. Participants' characteristics for subjective measures. Bold means statistical significance.

	Guided Imagery Group (N = 20)		Mental Task Group (N = 28)		Statistical Test		
Measures	**M**	**SD**	**M**	**SD**	**F**	***p***	**η^2**
Anxiety measures (pre-test)							
STAI Trait	45.00	7.91	45.93	33,117	0.12	n.s.	n.s.
STAI State	39.85	9.98	40.29	31,959	0.15	n.s.	n.s.
Motivational and affective measures							
Helplessness (pre-test)	18.00	5.48	17.3	4.94	0.41	n.s.	n.s.
Stress reduction (before–after)	2.25	5.27	1.00	1.52	**5.12**	**0.03**	0.102
Relaxation increase (after–before)	2.25	5.17	1.15	2.67	2.28	0.14	0.048

For the anxiety measures (STAI Trait and STAI State) at pretest, there were no significant differences between the groups. For helplessness, there was also no significant difference between the groups. However, there was a significant difference in the stress reduction. An ANOVA showed a significant difference between the two groups ($p < 0.05$, $\eta^2 = 0.102$), indicating that the GI group had a greater reduction in stress levels compared to the mental task group. Finally, there was a marginally significant difference in the relaxation increase between the two groups, with the GI group showing a greater increase in relaxation.

The 14th min of the GI session was chosen for analysis using the general linear model (GLM) classifier because it was found to be the time when participants were in the deepest state of relaxation. The GLM was able to distinguish between relaxation and mental states with 80% accuracy [98], and the results showed that the 14th min had a local maximum for both GI and mental task sessions, making it an appropriate time for further analysis to find if a higher alpha power was significantly correlated with a better performance in attentional tests such as the numerical Stroop, anti-saccade, and Go/No-go tasks.

Table 2 presents the results of a study that compared two different interventions, GI and mental tasks, on brain wave patterns and attentional control measures.

The participants were 48 individuals, with 20 randomly assigned to the GI group and 28 to the mental task group. The following measures were collected for both groups: alpha power and Beta power brain wave activity at the 14th min of the intervention, attention control, numerical Stroop task (% errors), anti-saccade task (% errors), and Go/No-go task (% errors).

Table 2 presents the results of comparing the GI group and the mental task group in terms of brain waves and attentional control measures. The table includes the means and standard deviations of the alpha and Beta power in the 14th min of the GI and mental task groups, as well as the scores in the attention control measures. The ANOVA results include F-values, p-values, and effect sizes (η^2) for each measure. The results indicate a significant difference in the GI group, where we can observe a higher alpha power compared to the mental task group, which was statistically significant (F = 5.23, p = 0.023). However, there was no significant difference in beta power between the two groups. Referring to attentional control measures, the GI group had lower errors on the numerical Stroop task compared to the mental task group, and this difference was statistically significant (F = 8.06, p = 0.007, η^2 = 0.146). Similarly, the GI group had lower errors in the anti-saccade task compared to the mental task group, and this difference was also statistically significant (F = 7.31, p = 0.010, η^2 = 0.135). Although the GI group did not show significant improvements in the Go/No-go task, it is possible that this discrepancy can be explained by differences in the cognitive demands of the tasks. The Go/No-go task requires both response inhibition and working memory, whereas GI may not enhance the working memory to a sufficient degree.

Table 2. Participants' characteristics for brain waves and attentional control measures. Bold means statistical significance.

Measures	Guided Imagery Group (N = 20) M	SD	Mental Task Group (N = 28) M	SD	Statistical Test F	p	η^2
Brain waves							
Alpha power (14th min)	0.25	0.13	0.17	0.12	**5.23**	**0.023**	0.105
Beta power (14th min)	0.08	0.03	0.07	0.03	1.23	n.s.	n.s.
Attention control							
Numerical Stroop task (% errors)	1.35	1.92	3.24	2.51	**8.06**	**0.007**	0.146
Anti-saccade task (% errors)	1.87	3.16	4.42	3.16	**7.31**	**0.010**	0.135
Go/No-go task (% errors)	7.33	6.72	8.85	5.93	0.70	n.s.	n.s.

The results suggest that GI may be more effective for enhancing attentional control in specific contexts, as it increases the alpha power and reduces stress levels through mental rehearsal and visualization, rather than through sustained focus practice like meditation.

The final analysis that was conducted in the described study is the Pearson's R correlations, verifying the strength and direction of the relationships between different variables.

Table 3 presents the correlations between seven variables measured in the study. Variable 1 represents alpha power at the 14th min, while variables 2 and 3 represent errors in the numerical Stroop and anti-saccade tasks, respectively. Variable 4 represents stress reduction, variable 5 represents helplessness, and variables 6 and 7 represent the STAI Trait and STAI State anxiety measures, respectively. The correlation coefficients range from −1 to 1, with −1 indicating a perfect negative correlation, 0 indicating no correlation, and 1 indicating a perfect positive correlation. For example, the correlation between the alpha power and numerical Stroop error is −0.35, which indicates a negative correlation. As the alpha power increases, the numerical Stroop error tends to decrease.

The results indicate that there was a significant negative correlation between alpha power at the 14th min and errors on the numerical Stroop task and anti-saccade task, suggesting that a higher alpha power was associated with better performance in these tasks.

Additionally, there was a significant positive correlation between stress reductions and helplessness, indicating that higher levels of stress reduction were associated with lower levels of helplessness. Furthermore, the anxiety measures (STAI Trait and STAI State) were positively correlated with each other and with the anti-saccade task and the numerical Stroop task. This suggests that higher levels of anxiety were associated with poorer performances in these attentional control tasks. Notably, the correlation between the STAI State anxiety measure and the alpha power at the 14th min was also significant, indicating that a higher anxiety was associated with a lower alpha power. Overall, these findings highlight the complex relationships between brain wave activity, attentional control measures, stress reduction, helplessness, and anxiety. Further research is needed to better understand these relationships and their potential implications in cognitive functioning and mental health.

Table 3. Correlations between measures. Note: * $p < 0.05$, ** $p < 0.01$. Bold means statistical significance.

Variable	1	2	3	4	5	6	7
1. Alpha power 14 min	-						
2. Num. Stroop (% errors)	**−0.35** **	-					
3. Anti-Saccade (% errors)	**−0.45** **	**−0.38** **	-				
4. Stress Reduction	**0.29** *	−0.03	−0.22	-			
5. Helplessness	0.24	−0.12	−0.04	**0.29** *	-		
6. STAI Trait	−0.12	0.10	0.27	0.10	**0.48** **	-	
7. STAI State	0.14	0.01	0.12	0.21	**0.37** **	**0.74** **	-

Two mediation models were employed to investigate how GI affects erroneous responses in the Stroop and anti-saccade tasks via alpha power at the 14th min. The findings indicate that alpha power at the 14th min acts as a dependable mediator between GI and the number of errors made in both attentional tasks, namely Stroop and anti-saccade tasks.

The mediation model (Figure 3) suggests that the relationship between GI and the Stroop test is mediated by the alpha power at the 14th min. Specifically, the significant negative coefficient between GI and the Stroop test suggests that GI leads to a better performance in the Stroop test and GI is a reliable mediator of the relationship.

Based on a mediation analysis (Figure 4), the model suggests that the relationship between GI and errors in the anti-saccade test is partially explained by changes in the alpha power. A mediation analysis suggests that an increase in the alpha power is associated with a reduction in errors in the anti-saccade test.

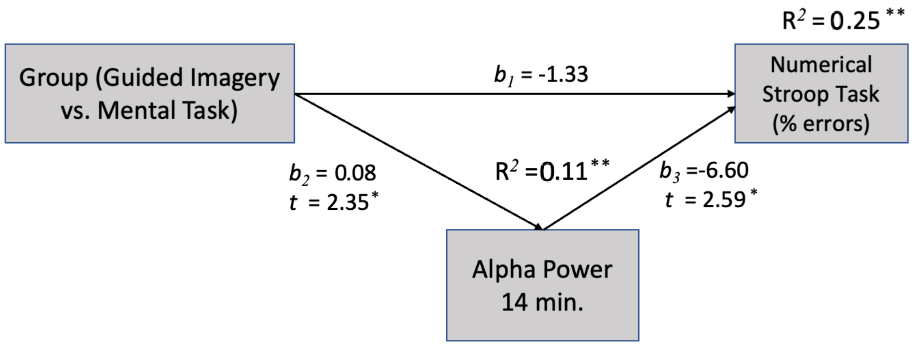

Figure 3. The effect of GI on reducing erroneous reactions in the Stroop test is mediated by the alpha power at 14 min. * $p < 0.05$, ** $p < 0.01$.

The significance of the t-values indicates that the coefficients are unlikely to have occurred by chance, supporting the relationships between the variables in the mediation model. These results suggest that the use of GI may improve cognitive performance, particularly in tasks requiring inhibitory control, by increasing the alpha power. However, further research is needed to confirm these findings and explore the underlying mechanisms of this relationship.

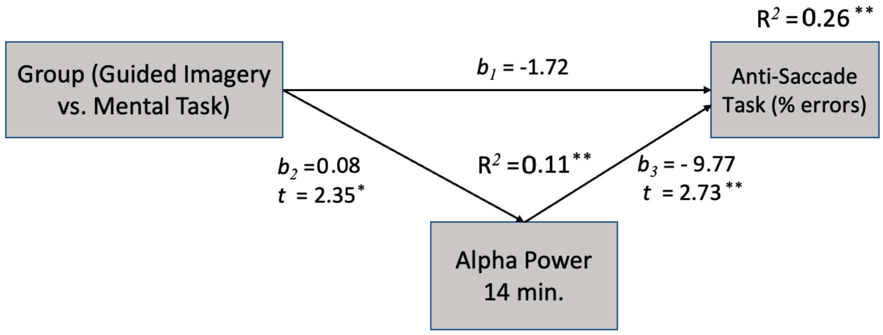

Figure 4. The effect of GI on reducing erroneous reactions in the anti-saccade test is mediated by the alpha power at 14 min. * $p < 0.05$, ** $p < 0.01$.

5. Limitations of the Study

The study is subject to several limitations that should be considered in the interpretation of the findings. Firstly, the relatively small sample size employed in this study may constrain the generalizability of the results to larger populations or different demographic groups. Consequently, caution should be exercised when extrapolating the findings to broader contexts. Furthermore, the study primarily focused on healthy male participants with no prior experience with guided imagery sessions and no chronic medical conditions. Consequently, the extent to which the results can be applied to other populations or individuals with specific health conditions may be limited. Additionally, the study primarily examined the short-term effects of the guided imagery session, with limited investigations into the long-term or sustained benefits. Future research should address this limitation by investigating the durability of the observed effects over an extended period. It is worth considering for future studies the inclusion of an additional control group that receives either no intervention or an alternative intervention. The absence of such a control group in this study poses challenges in isolating the specific effects of guided imagery from other potential factors.

Taken together, these limitations underscore the need for future research with larger and more diverse samples, longer follow-up periods, and additional control groups. By addressing these methodological considerations, a more comprehensive understanding of the effectiveness and potential limitations of guided imagery can be achieved, not only in the context of stress management but also in terms of enhancing attentional control test results. Such investigations will provide valuable insights into the broader cognitive benefits of guided imagery and further enhance its potential as a therapeutic intervention.

6. Conclusions

This study investigated the effects of the GI relaxation technique on cognitive and emotional measures and explored potential correlations between these measures. Guided imagery offers a distinct experiential approach to mindfulness and mental well-being. While meditation primarily focuses on cultivating present-moment awareness and detachment from thoughts, guided imagery involves actively engaging the imagination to create vivid sensory experiences [99]. This approach can be particularly helpful for individuals who find it challenging to quieten the mind or those who benefit from more structured practices. A further exploration of guided imagery is worthwhile as it broadens our understanding of mindfulness, offers customization, and provides a complementary practice to enhance overall mental health [100]. The robust findings from this research provide compelling evidence supporting the efficacy of guided imagery (GI) as an intervention for stress reduction and relaxation, surpassing the effects observed in the mental task group. Notably, the GI group exhibited significantly higher levels of alpha power, a key indicator of brain wave activity associated with improved attentional control. The strong correlation between alpha power and enhanced performances in attentional tasks further reinforces the potential benefits of GI in optimizing cognitive functioning. These findings underscore the significance of incorporating the GI technique in stress management protocols and highlight its promising role in enhancing attentional control abilities. The findings obtained in this study align with the existing literature, providing consistent evidence that an increase in alpha power is associated with an improved performance in attentional tests. Moreover, the observed reduction in stress levels resulting from the guided imagery (GI) intervention contributes to enhanced attentional processes by mitigating the distraction caused by anxiety-related thoughts or worries. These results highlight the beneficial impact of GI on attentional functioning and support its potential as an effective strategy for optimizing cognitive performance in stress-inducing contexts.

Based on the findings of this study, the formulated hypotheses put forth by the researchers were supported. The guided imagery (GI) intervention resulted in an increase in alpha power and improved performances in attentional tests, specifically the Stroop and anti-saccade tasks. It is worth noting that the lack of significant improvements in the Go/No-go task can be attributed to the varying attentional demands across different tests. As previously described, these attentional tests assess distinct types of attentional control. For instance, the numerical Stroop task measures attentional inhibition, which involves suppressing irrelevant information and focusing on relevant stimuli. The anti-saccade task assesses attentional shifting, which pertains to the ability to shift attention from one target to another. On the other hand, the Go/No-go task evaluates attentional vigilance, which involves sustaining attention over time and responding selectively to relevant stimuli while ignoring irrelevant ones.

In contrast to mindfulness practices, GI does not enhance focused attention but rather involves the visualization of pleasant images which elicit stress- and anxiety-reducing responses, potentially influencing the alpha power. It is noteworthy that the alpha power has been found to be positively correlated with information processing speeds [101]. The results suggest that the GI intervention may have had a more pronounced effect on cognitive flexibility, which could have contributed to the improved performances in the Stroop and anti-saccade tasks. These findings highlight the unique cognitive mechanisms engaged during GI intervention and its potential to enhance cognitive flexibility in a manner distinct from traditional mindfulness practices. The mediation model examining the relationship between GI, alpha power at the 14th min, and performance on the Stroop and anti-saccade tests provides a comprehensive understanding of the interplay between these variables. It sheds light on the potential mechanisms through which GI can affect cognitive performance, particularly in the context of attentional control tasks. In summary, the mediation model presented here offers a valuable structure for comprehending the intricate associations between GI, alpha power, and cognitive performance. It underscores the necessity for additional investigations to gain a deeper understanding of this domain. In particular, pairwise comparisons methods (analyzed for accuracy by Koczkodaj [102]) can be considered.

In conclusion, this study offers valuable insights into the potential advantages of guided imagery (GI) as an intervention for enhancing cognitive performance and emotional well-being. The findings contribute to the expanding body of research on cognitive and emotional interventions, providing valuable knowledge that can inform the development of effective interventions targeting cognitive and emotional functioning. Further investigations are warranted to examine the long-term effects of GI interventions and delve deeper into the potential associations between these cognitive and emotional measures. Such research endeavors would help advance our understanding of the sustained effects and the intricate interplay between cognitive and emotional domains, ultimately contributing to the refinement of interventions aimed at promoting overall cognitive and emotional well-being.

Moreover, a notable feature of this research involved the application of multi-sensor EEG signal classification and a GLM for the categorization of two mental states. These findings offer compelling evidence regarding the potential for developing innovative therapies in the domain of human–machine interactions like in [103] and that EEG is not the only medium that can be used to support human–machine interaction control [104,105]. For instance, the study titled "Golden Subject Is Everyone: A Subject Transfer Neural Network for Motor Imagery-based Brain Computer Interfaces" [106] explores the use of neural networks to transfer knowledge between individuals in the context of motor-imagery-based brain–computer interfaces. The researchers propose a new approach that allows data from one participant to be used to train a neural network, which can then be applied to predict and interpret brain signals from a different participant. The findings indicate that this method has potential and could lead to the development of more inclusive and widely applicable brain–computer interfaces.

Author Contributions: K.Z.: meaningful participation in the key phases of research and publication process, research project conceptualization, verification of results and analysis, manuscript writing, responses to reviewers, literature review, and implementing the GI relaxation technique; G.S.: research idea, selection of participants in the cohort, and statistical analysis; K.W.: EEG recordings, work in the laboratory, and data analysis; F.P.: EEG recordings, work in the laboratory, and data analysis; G.M.W.: head of the project, experiment idea and coordination, data science pipeline design, and manuscript writing. All authors have read and agreed to the published version of the manuscript.

Funding: The research presented herein was supported by the City of Lublin as a part of the cooperation of Lublin City Hall and Maria Curie-Sklodowska University towards a pilot study for the VRMed project. The authors would like to thank Ewa Lewandowska and Marek Rudziński of VRMed for fruitful discussions, inspiration, and the possibility of working together on new ideas.

Informed Consent Statement: The studies involving human participants were reviewed and approved by the Maria Curie-Sklodowska University Bioethical Commission (MCSU Bioethical Commission permission 9 July 2021). The patients/participants provided their written informed consent to participate in this study. Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The raw data supporting the conclusions of this manuscript will be made available by the authors without undue reservation to any qualified researcher.

Conflicts of Interest: The authors declare no conflict of interest.

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6.4 Recurrent and Convolutional Neural Networks in Classification of EEG Signal for Guided Imagery and Mental Workload Detection

arXiv:2405.16901v2 [cs.LG] 28 May 2024

Recurrent and Convolutional Neural Networks in Classification of EEG Signal for Guided Imagery and Mental Workload Detection

Preprint. Under review.

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Abstract

The Guided Imagery technique is reported to be used by therapists all over the world in order to increase the comfort of patients suffering from a variety of disorders from mental to oncology ones and proved to be successful in numerous of ways. Possible support for the therapists can be estimation of the time at which subject goes into deep relaxation. This paper presents the results of the investigations of a cohort of 26 students exposed to Guided Imagery relaxation technique and mental task workloads conducted with the use of dense array electroencephalographic amplifier. The research reported herein aimed at verification whether it is possible to detect differences between those two states and to classify them using deep learning methods and recurrent neural networks such as EEGNet, Long Short-Term Memory-based classifier, 1D Convolutional Neural Network and hybrid model of 1D Convolutional Neural Network and Long Short-Term Memory. The data processing pipeline was presented from the data acquisition, through the initial data cleaning, preprocessing and postprocessing. The classification was based on two datasets: one of them using 26 so-called cognitive electrodes and the other one using signal collected from 256 channels. So far there have not been such comparisons in the application being discussed. The classification results are presented by the validation metrics such as: accuracy, recall, precision, F1-score and loss for each case. It turned out that it is not necessary to collect signals from all electrodes as classification of the cognitive ones gives the results similar to those obtained for the full signal and extending input to 256 channels does not add much value. In Disscussion there were proposed an optimal classifier as well as some suggestions concerning the prospective development of the project.

Keywords guided imagery · mental workload · EEG · CNN · LSTM

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1 Introduction

Relaxation methods proved to be helpful for the patients with some illnesses and mental disorders. Oncological patients were reported to respond better to treatment when they used relaxation techniquesEremin et al. [2009]. Therefore, it is beneficial to develop relaxation techniques in order to improve the quality of life. Moreover Guided Imagery can be used as relaxation technique. It is largely applied and proved to be effective in reducing test anxiety and dealing with stress of different originsUrech et al. [2010], Stephens [1992], Nguyen and Brymer [2018]. Electroencephalography (EEG) can be a good method to find out if patients are in the state of relaxation or not. Scalp EEG is a non-invasive method of measuring bio-electrical activity of the human brain. Moreover, it is less expensive and less stressful for patients than other brain activity measuring devices, such as PET or MRIMurphy and Brunberg [1997], Sanei and Chambers [2021]. On the other hand, manual multichannel EEG signal analysis can be a difficult and time-consuming process. Machine learning and deep learning tools are commonly used to classify various types of data, starting with the imagesKrizhevsky et al. [2017] to the different kinds of signalsNasrullah and Zhao [2019], Cheng et al. [2021]. The aim of this study is to propose an EEG signal classifier based on the 1D Convolutional Neural Networks (CNNs) by using raw signal with only basic filtering done as an input data.

For different types of EEG signals, classical machine learning (ML) methods, such as Support Vector Machines (SVM), were used Bayram et al. [2013]. In classification of relaxation and concentration states based on the electroencephalographic signal SVMs can achieve around 80% of accuracy (ACC)You [2021].

State-of-the-art classification methods applied for the EEG signal already used Convolutional Neural Networks (CNNs) with success Oh et al. [2019]. Furthermore, the above mentioned classical ML methods are increasingly being replaced by deep learning approaches. Convolutional Neural Networks are applicable in the EEG signal analysis, for instance, in motor imagery processing Xu et al. [2019], epileptic seizure detection Zhou et al. [2018], emotion recognition Zhang et al. [2020], and research topics devoted to Brain-Computer Interfaces based on EEG feature extraction using CNNs Chen et al. [2023], among others, even for identity authentication Zhang et al. [2022].

The most common approach is to classify signals by feeding the classifier with the frequency bands data. The EEG signal is commonly partitioned into discrete frequency ranges, encompassing delta waves below 4 Hz, theta waves ranging from 4 to 7 Hz, alpha waves spanning 8 to 12 Hz, beta waves between 13 and 30 Hz, and gamma waves surpassing 30 Hz. It was proved that using specific selected bands of EEG signal, SVM classificator can be doneYou [2021], Li and Feng [2019]. Calculation of power across specific frequency bands is needed. Therefore it would be beneficial to skip manual feature extraction and use CNN-based feature extraction from the raw signal. Some researchers used this approach successfully for emotions recognitionChen et al. [2019], Yanagimoto and Sugimoto [2016]. The experiments described by Baydemir et al. showed that it is possible to classify EEG signal of low and high cognitive load using 1D-CNN with a great accuracyBaydemir et al. [2022]. Classification of fNIRS-EEG mental workload signal using CNN was made, showing a good accuracy of 89%Saadati et al. [2020]. However there are only few papers including 1D Convolutional Neural Networks used specifically in the binary classification of relaxation and mental workload using the raw EEG signal which still needs to be investigated.

In our previous research, the classical classification method was used for Guided Imagery and Mental Task groups Zemla et al. [2023]. Generalized Linear Model (GLM) used in that research achieved 81% accuracy using a very specific time segment, 779-839 seconds, extracted from the complete recording. In order to achieve this level of accuracy, this required feeding the classifier with five EEG bands (alpha, beta, delta, theta, and gamma), extracted from the raw signal of the 60 seconds duration. However, on the full-length recording, the accuracy of 90.77% was achieved.

The objective of this study is to compare four approaches to classification of EEG signals of two mental states: Guided Imagery relaxation technique and Mental Workload tasks. For this research 1D Convolutional Neural Network (1D-CNN), Long-Short Time Memory (LSTM), 1D-CNN-LSTM hybrid model and 2D-CNN (EEGNet) will be taken into consideration. Signals were filtered and split into 1-second segments. Bad channels were marked automatically and interpolated. That way all 256 channels could have been used for training. No further preprocessing or artifact removal was done. No features were extracted from that signal manually.

2 Materials and methods

The signal for this study was obtained from a cohort of 26 males, aged 19-24 years. They were all right-handed and short-haired. Being right- or left-handed could influence the results due to brain lateralization. Described experiments were reviewed and approved by the Maria Curie- Skłodowska University Bioethical Commission. The experiments were conducted according to the best experimental practices and guidelines. They were also done under the supervision of qualified psychologists. All participants agreed to the EEG signal recording and were informed about the purpose of the experiment. They all signed written consent before taking part in it.

2.1 Inclusion and exclusion criteria

The criteria for selecting participants in this study involve being a healthy, right-handed male, aged 19 to 24, with short hair and fluency in Polish. They should have no history of chronic diseases, no current use of prescribed or recreational drugs, and should be able to attend study appointments without specific technological requirements. Additionally, participants were required to abstain from alcohol and medication for at least 72 hours before the experiment.

On the other hand, exclusion criteria encompassed individuals younger than 19 or older than 24, left-handed individuals, those with long hair, limited proficiency in Polish, serious or chronic illnesses, current use of medications or drugs, recent medical treatments, or inability to attend study appointments. Participants failing to meet the inclusion criteria or declaring serious diseases, including mental disorders, were automatically excluded. Prior to participation, participants were informed about the EEG research and technology and consented to take part in the study.

There were several reasons for recruiting participants aged 19-24 and only males. Firstly, the majority of individuals in this age range are students, particularly those pursuing first and second degrees. Secondly, in the Institute of Computer Science, there is a predominant male student population, making it challenging to form both target and control groups including women. However, the most significant reason was the documented changes in women's EEG cortical activity throughout the menstrual cycle, as published by Solis-Ortiz et al. [1994], Krug et al. [1999]. These changes introduce additional variables into the model. Variations are observed in both alpha and beta bands Bazanova et al. [2014], Souza et al. [2022], which could be crucial for signal classification related to the individual's state of mind.

Moreover, it was noted that a substantial majority of female computer science students had lengthy hair. It is noteworthy that the research has also highlighted differences in electroencephalogram patterns between males and females Wada et al. [1994], Cantillo-Negrete et al. [2017], and the objective was to achieve a relatively balanced representation from the participant pool.

They all signed a written consent. Half of the group listened to the Guided Imagery relaxation recording prepared by the psychologist. The other half were asked to recall specific kinds of information: the names of Polish administrative units (voivodships), the names of the Zodiac signs, the names of US states, etc. (Mental Task group or MT group). Tasks were given by the same psychologist on the recording. After each task there was a period of silence when participants were thinking about the answer. The GI group was supposed to relax during the experiment, while the MT group was supposed to be put under mental workload. At the beginning of the experiment the MT group was told that after its completion they would be asked to write down all the information they will have recalled. The Guided Imagery and the Mental Task recordings were of the same length of 20 min. The participants were asked to close their eyes and each trial was conducted in the lying position with lights turned off to decrease the effects of muscle artifacts, power line noise and distractions on the EEG signal.

The experiments were conducted in the EEG Laboratory of the Department of Neuroinformatics and Biomedical Engineering of Maria Curie-Skłodowska University (UMCS) in Lublin, Poland (Figure 1). All trial signals were recorded at the sampling frequency of 250 Hz with the use of a 256-channel dense array EGI GSN 130 series cap (Figure 1). For signal acquisition, the EGI Net Station 4.5.4 software was used.

Our dense array amplifier recorded the signal from all 256 electrodes. However, we expected to find differences on the so-called cognitive electrodes based on the previous experience in the cognitive processing EEG signal analysis Wojcik et al. [2023], Kawiak et al. [2020a], Kwasniewicz et al. [2021], Schneider et al. [2022]. These electrodes are described in the EGI 256-channel cap specification Geodesics [2003, 2009, 2011] as the best for cognitive ERP observations, covering the scalp regularly, and numbered as follows: E98, E99, E100, E101, E108, E109, E110, E116, E117, E118, E119, E124, E125, E126, E127, E128, E129, E137, E138, E139, E140, E141, E149, E150, E151, and E152 (see Fig.2).

2.2 Signal preprocessing and data sets preparation

The recorded EEG signals were pre-processed using mne Python toolkit 1.3.0 Gramfort et al. [2013]. Noisy channels were removed from the signal and interpolated to maintain the same size of data in each sample. For automatic bad channel rejection the RANSAC algorithm implemented in pyprep toolkit Appelhoff et al. [2023] was used. This toolkit is based on the PREP pipeline designed for EEG signal preprocessing in MATLABBigdely-Shamlo et al. [2015]. The signal from each trial was filtered with a band pass filter of 1-45 Hz. Each signal was cropped from 10 to 12 minutes of the recording, which gives 120 seconds per subject. The time segment was chosen based on the previous experience with GI relaxation method. It was proved that the period between 10 and 14 min. of recording has the greatest significance for distinguishing the relaxation and mental workload state Zemla et al. [2023]. Each cropped signal was split into 1-second segments. This gives a total amount of 3,120 recording samples (1,560 samples of Guided Imagery group and 1,560 samples of Mental Task group). Figure 5 shows the data preparation steps. The sample 1-s segments for both GI

Figure 1: On the left: EGI 256-channel EEG cap.On the right: the overview of the whole EEG Laboratory at UMCS, Lublin, Poland

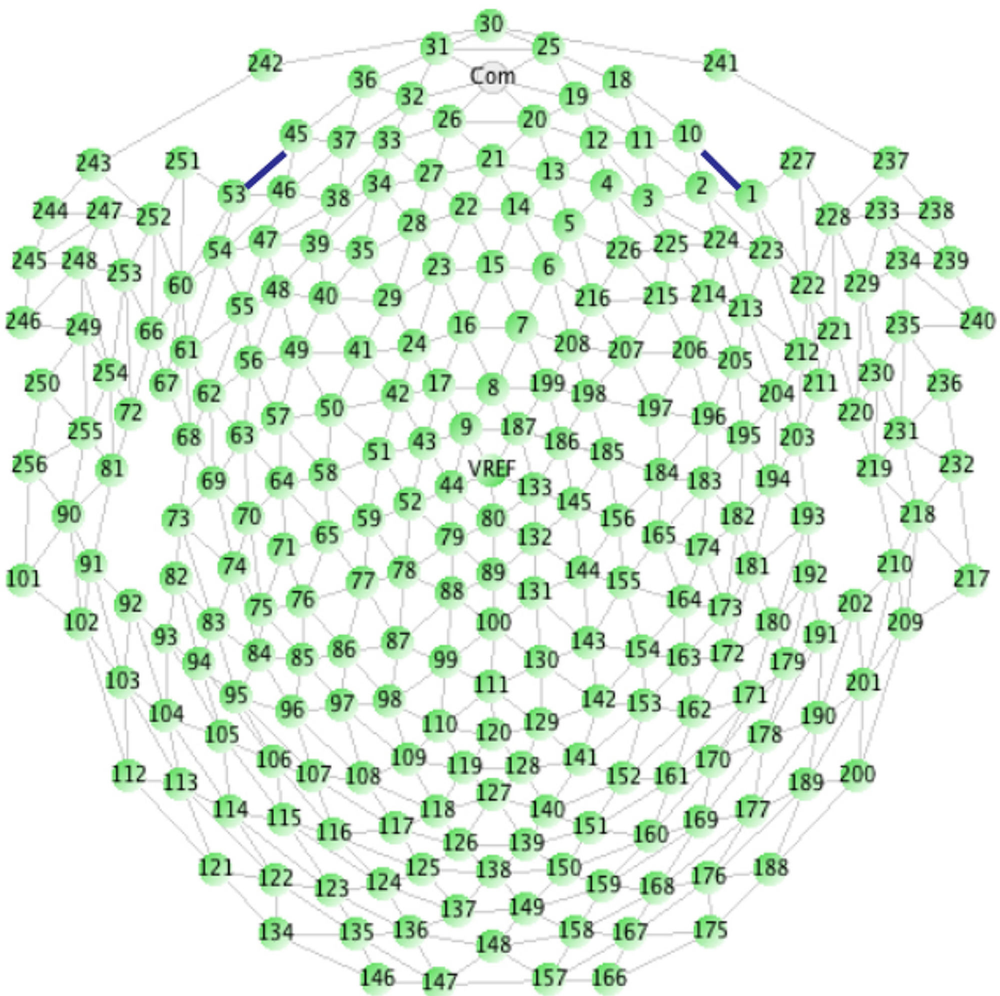

Figure 2: Electrodes placement on HydroCel GSN 130 Geodesic Sensor NetGeodesics [2009], Wojcik et al. [2023]

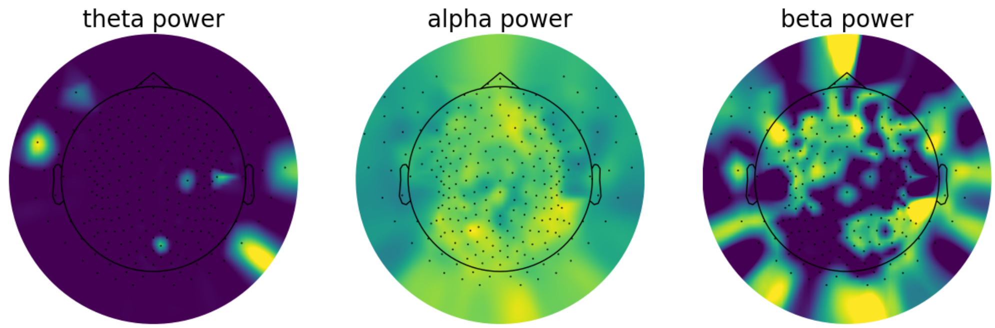

Figure 3: Power spectral density of different frequency bands shown for 1-s segment of signal from GI sample subject

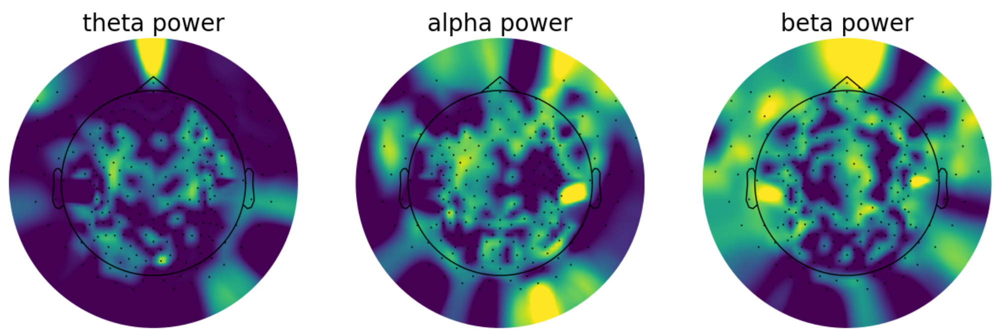

Figure 4: Power spectral density of different frequency bands shown for 1-s segment of signal from MT sample subject

and MT states were shown in terms of different power densities for each of frequency bands in Figures 3 (for GI) and 4 (for MT).

Two sets of electrodes were selected for the experiments. The first one included a full set of 256 channels of EEG signal. The second one contained a subset of 26 electrodes from the central-parietal region to reduce the amount of data subjected to training. Based on the previous research in analyzing cognitive processing of EEG signals Kawiak et al. [2020b], Kwaśniewicz et al. [2020], Schneider et al. [2022], variations were expected to be observed specifically on the

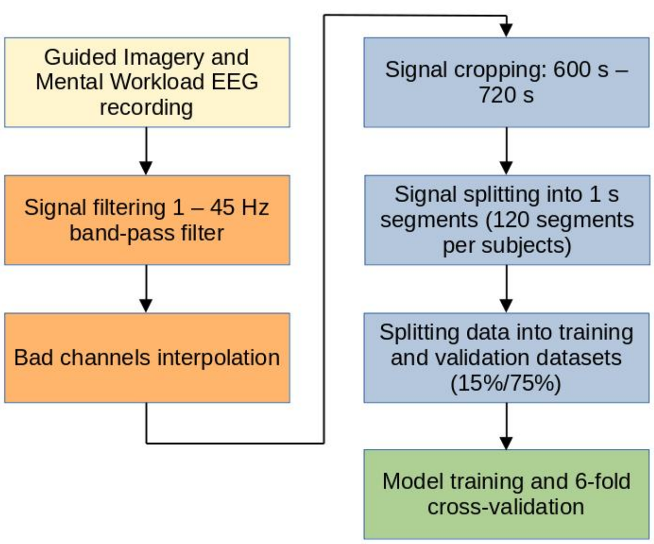

Figure 5: Data science pipeline - steps of data preparation for training

above mentioned 26 cognitive electrodes. Those electrodes, specified as optimal for observing cognitive phenomena according to the EGI 256-channel cap specifications EGI [2006], are positioned in the central-ocipital region and numbered: E98, E99, E100, E101, E108, E109, E110, E116, E117, E118, E119, E124, E125, E126, E127, E128, E129, E137, E138, E139, E140, E141, E149, E150, E151, and E152. The topographical map showing the placement of these electrodes on the scalp can be found in the EGI documentation EGI [2006] and in Wojcik et al. [2023], Fig. 1. It was also showed that they cover the region of the greatest significance for the alpha band-based research, as this band is correlated with the relaxation stateSanei and Chambers [2021]. Finally, the both datasets consisted of 3,120 signal samples. Each sample included 256 EEG channels in the data set 1 (FULL-256) or 26 EEG channels in the data set 2 (COGN-26), and 250 timesteps per second. No further pre-processing or feature extraction was done.

The data set was split into 2,640 samples in the training data set and 480 samples in the testing data set. 6-fold cross-validation was used to confirm performance of the model. The StratifiedGroupKfold method from scikit- learnPedregosa et al. [2011] was used to prevent the data from one subject to be put in training and validation data sets at the same time. On the other hand, StratifiedGroupKFold keeps the data set with a balanced number of samples for each group. The data set was shuffled to prevent the model from learning data from only one subject in one batch. Folds were saved for benchmarking purposes.

2.3 EEGNet

The first method of classification of EEG signal in this research was 2D-CNN architecture called EEGNet proposed by Lawhern et al.Lawhern et al. [2018]. Implementation of this network was done using tensorflow and keras. All architecture remained as presented in the original research. The parameters were adjusted as suggested by the EEGNet authors. All parameters are described in table Table 1 and are given in Figure 6.

The learning rate was set to 0.001, the optimizer was Adam and the loss function was binary cross-entropy. Loss function selection resulted in changing the activation function from original Softmax to Sigmoid.

EEGNet performance in terms of validation accuracy and validation loss was selected as reference for all other methods of binary classification described in this research. Using COGN-26 data set, the model had 2,153 parameters. After training on FULL-256 data set the model had 6,753 parameters.

Parameter	**Description**	**Value**
F1	Number of temporal filters	8
F2	Number of pointwise filters	16
k	Kernel length	125
D	Number of spatial filters for each temporal convolution	2 (original value)
-	Activation function in output layer	Sigmoid

Table 1: Parameters set for EEGNet architecture according to original paperLawhern et al. [2018]

2.4 LSTM

Long short-term memory (LSTM) is a type of Recurrent Neural Network cell introduced as a solution for learning features from long time sequences including noisy dataHochreiter and Schmidhuber [1997].

The simple LSTM-based network was tested as a second reference method. It was proved that Bidirectional LSTM-based (BiLSTM) model can be a good method of EEG classification tasks like emotion classificationYang et al. [2020] or seizure classificationHu et al. [2020].

The architecture presented here contained one BiLSTM layer having 64 units(cells) for each backward and forward direction. The number of units were selected according to Yang et al. [2020]. As the input signals included 250 samples each, we decided to take 1/4th of the sampling rate as a unit number. The closest power of 2 was 64. In the backward and forward directions, this means that our model included of 128 units in BiLSTM configuration. Two fully-connented (called also dense) layers, of 32 and 1 node, followed BiLSTM layer. Between those layers, dropout layer was set as the regularization method. Dropout rate was set to 0.5. Activation function in output Fully Connected layer was Sigmoid. The selection of power of two as the unit number in the LSTM layer was supported by connecting CNNs and LSTM in the next step. The selection of 32 nodes in the first Fully Connected layer was supported by trials with different sizes of 16, 32, 64 and 128. That number in that BiLSTM configuration gave the best results.

The learning rate was set to 0.001, the optimizer was Adam and the loss function was binary cross-entropy.

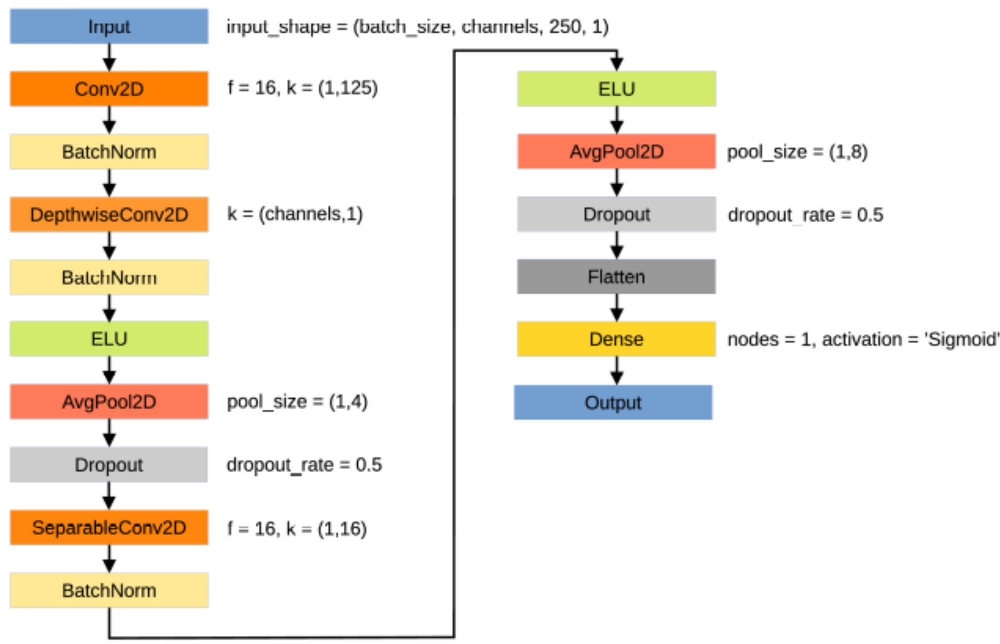

Figure 6: EEGNet detailed model architecture with parameters for specific layers: f - number of filters, k - kernel size, pool sizes and dropout rates.

Using the COGN-26 data set, the model had 50,753 parameters. After training using the FULL-256 data set, the model had 168,513 parameters. Detailed architecture is given in Fig. 7.

2.5 1D-CNN

The proposed CNN model included of 4 convolutional layers. The layer is the main element of Convolutional Neural Network. It contains a set of filters which adjust their parameters during the model training phase. The LeakyReLU activation layer was used after each convolutional layer to provide non-linearitySchmidhuber [2015]. Moreover, the Batch Normalization layer was used in each block of convolution containing a convolution layer and an activation layer. The purpose of Batch Normalization is to normalize data in batch to enhance learning speed and performance. Batch Normalization was neglected in the third block of convolution because Spatial Dropout (called SpatialDrop in Fig. 8) with the dropout rate of 0.25 was used before. Spatial Dropout is a method of regularization that drops randomly features learned by convolution layer during training to reduce overfittingSanghun and Chulhee [2020]. Instead of using pooling layers, strided convolution was applied. It can provide simpler architecture with better accuracy in some applicationsSpringenberg et al. [2014]. In the case of proposed CNN model it was the best choice in terms of achieved accuracy. The Flatten layer was set in front of two Fully Connected layers, which are responsible for binary classification of features extracted by convolutional layers. The dropout layer was used between Fully Connected layers as regularization method. It deactivates randomly weights of certain parameters during the training process to reduce overfittingSrivastava et al. [2014]. The dropout rate was set to 0.5.

For the 1D-CNN model the loss function and optimizer remain the same as for the EEGNet and LSTM-based model. The learning rate was reduced to 0.00001 from the default value of 0.001.

The numbers of parameters in the model for COGN-26 and FULL-256 data sets were: 165,649 and 176,689 respectively. Figure 8 shows the model architecture in detail.

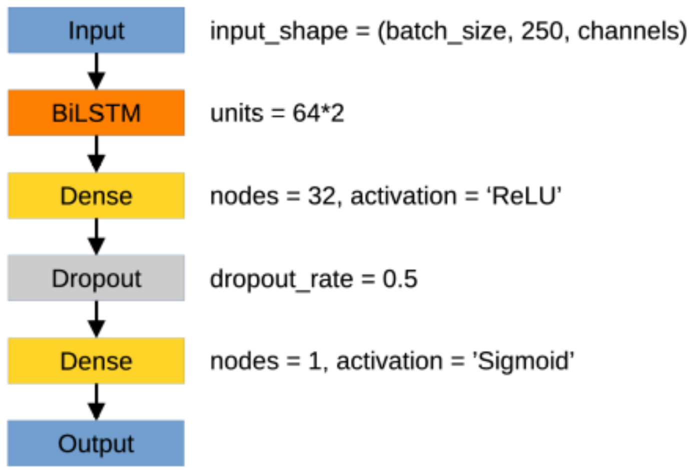

Figure 7: LSTM detailed model architecture with parameters of specific layers

2.6 1D-CNN-LSTM

It was proved that 1D-CNN-LSTM can be applied to the EEG signals successfully. It was reported that this kind of approach can be beneficial for epileptic seizures classification Xu et al. [2020] and motor imagery classification Li et al. [2022].

A decision was made to connect 1D-CNN network model with the LSTM one described in the previous sections. In order to pass the Flatten output as input to the BiLSTM layer, and mantain the same model weights for all output data, the Time Distributed layer was used (referenced in Figure 9 as TimeD. Moreover as data are processed in CNN layers and the input size for LSTM part is already reduced, we decided to reduce number of nodes in first Fully Connected layer from 64 to 32. This resulted in model architecture shown on Figure 9.

The numbers of parameters in the model for the COGN-26 and FULL-256 data sets were: 77,777 and 88,817 respectively. The learning rate, optimizer and loss function were set as for 1D-CNN model.

2.7 Evaluation metrics

Validation accuracy was selected as the main performance metric due to the fact that the balanced data sets were used for the binary classification. Validation loss was also monitored during the model designing phase. F1-score, precision and recall averaged over 6 folds are also reported for all tested models. Mentioned metrics are defined as followsHossin and Sulaiman [2015]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Here TP is defined as True Positives, TN - True Negatives, FP - False Positives and FN - False Negatives.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

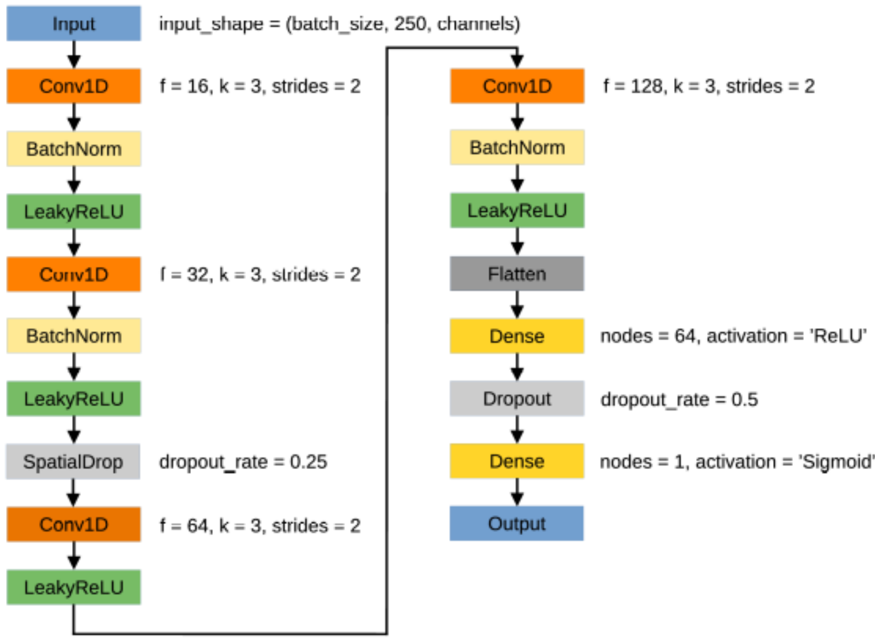

Figure 8: Detailed 1D-CNN model architecture with parameters of specific layers: f - number of filters, k - kernel size, pool sizes and dropout rates

Precision quantifies the accurate prediction of positive labels within the total predicted labels belonging to the positive class.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

Recall is a measure of the number of positive labels that are correctly classified.

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} = \frac{2 * TP}{2 * TP + FP + FN} \tag{4}$$

F1 is defined as the harmonic mean between the recall and precision values.

Results

All architectures were tested using keras and tensorflow 2.15 packages with Python 3.11. The hardware used for testing was an Intel i7-based machine with 64GB of DDR5 RAM. The machine was also equipped with the Nvidia GeForce RTX 4070-based graphics card with 12GB of RAM. The operating system was Ubuntu 23.10. None of the setup elements were overclocked.

EEGNet was chosen as a reference because of the well documented architecture. The 6-fold cross validation procedure was perofmed using the model. The results for each fold and validation metrics such as: accuracy, loss, F1-score, precision and recall as well as their average values with standard deviations are presented in Tables 2 and 3 - for the FULL-256 and COGN-26 data sets. On the average after the 6-fold cross-validation EEGNet obtained 0.7615 and 0.7646 accuracy respectively. In terms of precision as well as recall and F1-score with all average metrics exceeding 0.75 on both data sets model can be considered as a good reference point.

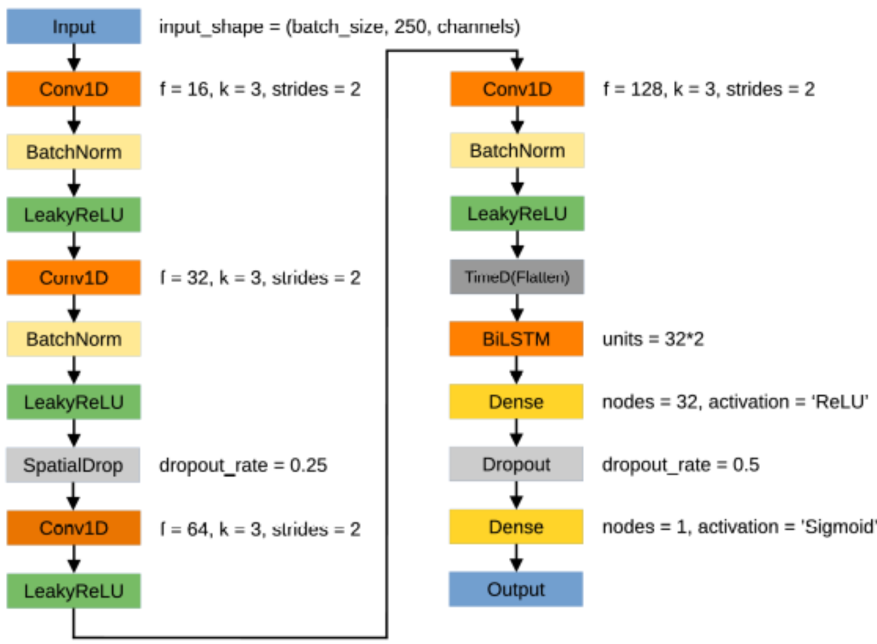

Figure 9: 1D-CNN-LSTM detailed model architecture with parameters of specific layers: f - number of filters, k - kernel size, pool sizes and dropout rates.

Table 2: EEGNet Validation Metrics for FULL-256 data set for each

Fold	ACC	Loss	F1-score	Precision	Recall
1	0.7917	0.4186	0.8016	0.7652	0.8417
2	0.7958	0.562	0.8293	0.7126	0.9917
3	0.7563	0.6193	0.7053	0.8917	0.5833
4	0.6458	0.9923	0.7195	0.5956	0.9083
5	0.8375	0.3612	0.8465	0.8022	0.8958
6	0.7417	0.655	0.6575	0.9754	0.4958
Avg	0.7615	0.6014	0.7600	0.7905	0.7861
Std.	0.0658	0.2230	0.0764	0.1336	0.1989

The LSTM model with only one LSTM layer followed by dropout was chosen as second reference point. The results 6-fold cross-validation and validation metrics such as: accuracy, loss, F1-score, precision and recall as well as their average values with standard deviations are presented in Tables 4 and 5. On the FULL-256 data set precision, recall and F1-score achieved the averaged over folds values above 0.72. The averaged ACC for this case was 0.7250 on the full set of channels. The model performed worse than EEGNet in terms of all described metrics. On the data set containing only 26 electrodes it performed the worst of all compared models with the cross-validated accuracy of 0.6833. It achieved also the worst cross-validated accuracy for both data sets.

The 6-fold cross validation procedure was applied for the 1D-CNN model. The results for each fold and validation metrics such as: accuracy, loss, F1-score, precision and recall as well as their average values with standard deviations are presented in Tables 6 and 7. The averaged over folds accuracy for this model using the FULL-256 data set was 0.7682 which can be considered as a result comparable to that of the EEGNet model. On cognitive electrodes subset

Table 3: EEGNet Model Validation Metrics COGN-26 data sets for each fold

Fold	**ACC**	**Loss**	**F1**	**Precision**	**Recall**
1	0.5312	0.6879	0.5455	0.5294	0.5625
2	0.7729	0.8835	0.8149	0.6877	1.0000
3	0.6812	0.7774	0.5321	1.0000	0.3625
4	0.9042	0.2666	0.8996	0.9450	0.8583
5	0.7917	0.3944	0.8270	0.7071	0.9958
6	0.9063	0.2442	0.9036	0.9295	0.8792
Avg	0.7646	0.5423	0.7538	0.7998	0.7764
Std.	0.1427	0.2755	0.1705	0.1856	0.2579

Table 4: LSTM Model Validation Metrics on FULL-256 data set for each fold

Fold	**ACC**	**Loss**	**F1**	**Precision**	**Recall**
1	0.6417	1.3984	0.7346	0.5833	0.9917
2	0.7479	0.7055	0.7881	0.6798	0.9375
3	0.7771	0.7453	0.8022	0.7209	0.9042
4	0.5417	2.434	0.5000	0.5500	0.4583
5	0.8854	0.3187	0.896	0.8200	0.9875
6	0.7563	0.6777	0.6777	1.0000	0.5125
Avg	0.725	1.0466	0.7331	0.7257	0.7986
Std.	0.1187	0.7644	0.1355	0.1658	0.2454

it achieved 0.8094 accuracy which outperforms all described architectures for this case. Also in terms of F1-score, precision and recall this model performs the best in the research for the COGN-26 data set.

The 6-fold cross validation procedure was applied for the hybrid 1D-CNN-LSTM model. The results for each fold and mentioned earlier validation metrics such as: accuracy, loss, F1-score, precision and recall as well as their average values with standard deviations are presented in Tables 8 and 9. The averaged over folds validation accuracy for this model trained using the FULL-256 data set was 0.7726. This was the best accuracy result for the full set of channels of all approaches discussed in this paper. On the cognitive electrodes subset it achieved 0.7556 accuracy which outperforms only the plain LSTM model in this case. For the COGN-26 data set the results are worse than those of 1D-CNN and comparable with EEGNet.

The averaged 6-fold cross-validated metrics for all models are reported in Tab. 10 for the FULL-256 data set and in Tab. 11 for the COGN-26 data set. It can be seen that the worst model for classification from the full set of electrodes is the one-layer LSTM-based model. The other models obtained comparable results in terms of accuracy, while the best one was the 1D-CNN-LSTM hybrid model. On the other hand for the signal collected from subset of cognitive electrodes in terms of validation metrics of accuracy, loss, F1-score and precision the 1D-CNN-based model outperformed all other approaches with the accuracy of 0.8094, the F1-score value of 0.7806 and the precision close to 0.8970.

Discussion

There are known approaches of using convolutional neural networks in biometrics Prakash et al. [2022] and other cybernetical tasks Daoui et al. [2023], more and more of them in the EEG signal classification Prakash et al. [2022]. More and more often deep learning methods are applied in the biomedical engineering systems to help patients with numerous of disorders like sleep apneua Kandukuri et al. [2023]

The aim of this paper was to compare the effectiveness of four different architectures in the EEG signal classification originating from a psychological experiment involving Guided Imagery. There were used the EEGNet, LSTM, 1D-CNN and 1D-CNN-LSTM approaches in the case of dense array amplifier setup using 256 electrodes and the so-called cognitive setup using 26 electrodes.

Training all of these models is relatively fast, does not require extensive resources, and as a result can be incorporated into less demanding computational environments after training using different data. What is also beneficial is that in spite of the fact that the EEG signal can vary in time and between subjects, it is possible to train the model with great

Table 5: LSTM Model Validation Metrics on COGN-26 data set for each fold

Fold	ACC	Loss	F1	Precision	Recall
1	0.6542	3.0136	0.7422	0.5916	0.9958
2	0.75	4.276	0.8	0.6667	1.0000
3	0.5729	5.629	0.5393	0.5854	0.500
4	0.5437	5.277	0.6803	0.5236	0.9708
5	0.8125	0.8726	0.8421	0.7273	1.0000
6	0.7667	2.267	0.6957	1.0000	0.5333
Avg	0.6833	3.5559	0.7166	0.6824	0.8333
Std.	0.1101	1.8403	0.1063	0.1709	0.2458

Table 6: 1D-CNN Model Validation Metrics on FULL-256 data set for each fold

Fold	ACC	Loss	F1	Precision	Recall
1	0.8758	0.3077	0.8745	0.8782	0.8708
2	0.7917	0.5703	0.8227	0.7160	0.9667
3	0.8375	0.4113	0.8169	0.9355	0.7250
4	0.6042	1.6410	0.6494	0.5828	0.7333
5	0.7625	0.5687	0.8034	0.6853	0.9708
6	0.7375	0.5966	0.6519	0.9672	0.4917
Avg	0.7682	0.6826	0.7698	0.7942	0.7931
Std.	0.0947	0.4828	0.0954	0.1547	0.1827

accuracy using smaller segments of 1 second instead of 1 minute or even the full-length signal. Benefit of this work is also that all the models make use of all 256 EEG channels to learn features and its simplified version of 26 cognitive channels.

Indeed, the results obtained in this study show that the manual feature extraction (EEG bands, wavelets etc.) can be neglected while using the CNN-based, LSTMs and hybrid models architectures.

Simple filtration and interpolation of the signal seem to be sufficient. The binary signal classifiers described above perform well on raw data, resulting in the level of accuracy comparable to that of state-of-the art methods and to our previous paper on Generalized Linear Model in EEG signal classification Zemla et al. [2023].

In case of the full signal collection recorded from 256 electrodes the 1D-CNN-LSTM performs best in terms of accuracy and precision. Almost as good as the one above is 1D-CNN, especially that it has better loss and F1-score values. One layer LSTM accuracy is the worst in this experiment, however still higher than 0.70 with the best recall of 0.79. The reference model EEGNet has the accuracy of 0.76 (compared to the best discussed here 0.77) and generally lower characteristics in the case of remaining three metrics. The collection and comparison of all results of the discussed classifiers are presented in Tab. 10.

In the case of the signal collected from 26 cognitive electrodes evidently the best one is the proposed 1D-CNN model achieving 80% accuracy with the best loss, F1 and precision characteristics. The one-layer LSTM has much lower accuracy (68%) but its recall is the highest reaching 0.83. The accuracy of the EEGNet reached 0.76 and 1D-CNN-LSTM 0.75 which were lower by 5% compared with the best one 1D-CNN. The other parameters like F1 and precision are of the same order of value, relatively similar but none is as good as that for 1D-CNN-LSTM. The collection and comparison of all results of the discussed classifiers are presented in Tab. 11.

Better performance on 26 electrodes (accuracy of 81% for 1D-CNN vs 77% for 1D-CNN-LTSM) can be the result of putting more influential data for feature extraction and automatically selecting those of greater significance for the task than the manually selected subset of 256 electrodes or in special case all of them.

Thus it was proved that from the computational point of view it is even more beneficial to collect fewer data for such tasks and expanding the cap to 256 electrodes does not always add a significant value.

There is still place for improving those models by training them with more data from more subjects. There is also need to test if best models work well for the data gathered from female subjects. Also finding new architecture for this task can be a way to reducing number of parameters of the model. It needs to be investigated how other electrodes

Table 7: 1D-CNN Model Validation Metrics on COGN-26 data set for each fold

Fold	**ACC**	**Loss**	**F1**	**Precision**	**Recall**
1	0.8833	0.2768	0.8848	0.8740	0.8958
2	0.7583	0.9046	0.8041	0.6761	0.9917
3	0.6854	0.7771	0.5519	0.9588	0.3875
4	0.9312	0.2232	0.9281	0.9726	0.8875
5	0.8188	0.4445	0.7981	0.9005	0.7167
6	0.7792	0.5075	0.7166	1.0000	0.5583
Avg	0.8094	0.5223	0.7806	0.8970	0.7396
Std.	0.0886	0.271	0.1341	0.1179	0.2312

Table 8: 1D-CNN-LSTM Model Validation Metrics for FULL-256 data set for each fold

Fold	**ACC**	**Loss**	**F1**	**Precision**	**Recall**
1	0.7292	0.6919	0.7789	0.658	0.9542
2	0.7500	1.069	0.7993	0.6676	0.9958
3	0.8583	0.3907	0.8373	0.9831	0.7292
4	0.7167	0.9444	0.7247	0.7047	0.7458
5	0.8875	0.2449	0.8945	0.8419	0.9541
6	0.6938	1.214	0.5638	0.9794	0.3958
Avg	0.7726	0.7591	0.7664	0.8058	0.7958
Std.	0.0803	0.3852	0.1144	0.1510	0.2268

subsets, like 10-20 international systemChatrian et al. [1985] can affect performance of classification using the described architecture.

Another aspect of improvements that can be applied is the parameter tuning for the models. In our opinion, based on the previous experience Wojcik et al. [2023] this could increase the accuracy of the models by 3%-5%.

Then, there can be designed more complex hybrid architectures, involving other methods of EEG signal analysis Kawala-Janik et al. [2014], Kahankova et al. [2017] or eg. the fuzzy logic approach Mikołajewska et al. [2017], Prokopowicz et al. [2017]

The research presented here can shed new light on the engineering of new brain-computer interfaces with application for psycho-therapists and neuro-therapists using the relaxation techniques and Guided Imagery method.

Acknowledgements

The authors would like to thank Ewa Lewandowska and Marek Rudziński of VRMed for fruitful discussions, inspiration and possibility of working together on new ideas.

Author contributions statement

F.P.: Principal Investigator of the project, research project conceptualization at applied neuroinformatics dimension, concept of convolutional neural networks application, data processing, data analysis, manuscript preparation, models design and implementation, EEG recordings; G.M.W.: Key Investigator of the research, research idea and methodological support, manuscript preparation; K.W.: EEG recordings, work in the laboratory; A.K.: statistical consultation; G.S.: research project conceptualization at psychological dimension; K.Z.: research project conceptualization at psychological dimension and implementing Guided Imagery relaxation technique.

Data availability statement

The raw data supporting the conclusions of this manuscript will be made available by the authors, without undue reservation, to any qualified researcher. To obtain the data please contact Filip Postepski using e-mail address: filip.postepski@mail.umcs.pl.

Table 9: 1D-CNN-LSTM Model Validation Metrics for COGN-26 data set for each fold

Fold	ACC	Loss	F1	Precision	Recall
1	0.7688	0.5999	0.7861	0.7312	0.9758
2	0.7542	1.3300	0.8027	0.6704	1.0000
3	0.7250	1.2670	0.6207	1.0000	0.4500
4	0.7771	0.5214	0.8165	0.6939	0.9917
5	0.7271	0.566	0.7207	0.7380	0.7042
6	0.7813	0.7457	0.7200	1.0000	0.5625
Avg	0.7556	0.8383	0.7445	0.8056	0.7807
Std.	0.0247	0.3648	0.0732	0.1526	0.2423

Table 10: Evaluation of Metrics for Different Models for the FULL-256 data set. The best result for every metric is reported in bold.

Model	ACC	Loss	F1	Precision	Recall
EEGNet	0.7615	0.6014	0.75995	0.79045	0.7861
LSTM	0.7250	1.0466	0.7331	0.7257	**0.7986**
1D-CNN	0.7682	**0.6826**	**0.7698**	0.7942	0.7931
1D-CNN-LSTM	**0.7726**	0.7592	0.7664	**0.8058**	0.7958

Additional information

Funding: This study was financed by Maria Curie-Sklodowska University as beneficiary of "UMCS Mini-Grants" programme in the academic year 2022/23.
Conflict of interest: No conflicts of interest are declared.
Ethics approval and consent to participate: The studies involving human participants were reviewed and approved by the Maria Curie- Skłodowska University Bioethical Commission. The participants provided their written informed consent to participate in this study.

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Table 11: Evaluation of Metrics for Different Models using the COGN-26 data set. The best result for each metric is reported in bold.

Model	ACC	Loss	F1	Precision	Recall
EEGNet	0.7646	0.5423	0.7538	0.7998	0.7764
LSTM	0.6833	3.5559	0.7166	0.6824	**0.8333**
1D-CNN	**0.8094**	**0.5223**	**0.7806**	**0.8970**	0.7396
1D-CNN-LSTM	0.7556	0.8383	0.7445	0.8056	0.7807

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