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

Katarzyna Zemła

Student number: S20021

ICT & Psychology

SWPS University of Social Sciences and Humanities &

Polish-Japanese Academy of Information Technology

Thesis prepared under the supervision of:

dr hab. Grzegorz Marcin Wójcik, prof. PJATK

prof. dr hab. Grzegorz Sedek

July 7, 2023

Abstract Guided imagery (GI) is a relaxation technique involving the use of mental imagery to evoke sensory experiences, has been the subject of extensive research in various fields. GI has several applications, including healthcare, sports psychology, and stress management. Despite the overall positive findings, some limitations exist in the literature on guided imagery. To address these limitations, we utilized dense array EEG apparatus during GI sessions, representing a novel approach that contributes valuable insights to the current state of literature in qualitative and quantitative aspects of GI influence on cortical activity and psychological indicators. It was demonstrated that GI influences brain wave activity, particularly by increasing alpha power. These changes indicate a shift towards a relaxed and attentive state. By combining EEG data with self-report measures of imagery vividness, emotion, and subjective experiences, we were able to establish a more comprehensive understanding of this technique. Furthermore, this approach allows for the use of Generalized Linear Models (GLMs) in guided imagery research, offering flexibility in classifying mental states based on neural patterns associated with guided imagery and mental task engagement, with potential implications for developing new Human-Machine Interaction therapies. Moreover, individuals in the GI group demonstrated improved performance on tasks involving attentional control, indicating enhanced cognitive functioning. Attention tests such as the Anti-saccade, Go/no-Go, and Stroop tasks provide a unique approach to evaluate the influence of guided imagery on enhancing attention and cognitive performance. Understanding more the effects of GI enhances our knowledge of its potential benefits for stress reduction, attentional regulation which are indispensable in the contemporary world characterized by rapid and incessant changes, a multitude of stimuli, and heightened levels of anxiety exposure.

Streszczenie Guided imagery (GI) to jedna z technik relaksacyjnych polegajaca na wykorzystaniu wyobraźni do wywoływania doznań sensorycznych, która ma wiele zastosowań, w tym w opiece zdrowotnej, psychologii sportu i zarzadzaniu stresem. Istnieja pewne ograniczenia w literaturze dotyczacej GI, dlatego podjete badanie miało na celu sprawdzenie czy możliwy jest ilościowy i jakościowy pomiar wpływu GI na aktywność kory mózgu i wskaźniki psychologiczne. W przeprowadzonym badaniu wykorzystana została elektroencefalografia (EEG) gestej matrycy, która umożliwiła obserwacje zmian fal mózgowych podczas interwencji GI. Zrozumienie wpływu GI na aktywność fal mózgowych dostarcza informacji na temat ukrytych mechanizmów neuronalnych zwiazanych z ta praktyka. Dodatkowo dane EEG zostały wzbogacone o samoopisowe miary emocji i subiektywnych doświadczeń, co pozwoliło nam uzyskać bardziej kompleksowe zrozumienie efektów sesji GI. Zebrane dane umożliwiły także zastosowanie GLMs (ang. Generalized Linear Model) pozwalajacych na klasyfikacje stanów mentalnych na podstawie wzorców neuronalnych zwiazanych z grupa poddana oddziaływaniu GI i wzorców zarejestrowanych dla grupy wykonujacej zadania mentalne/pamieciowe. Klasyfikacja oparta na EEG i modelowaniu GLM daje potencjał do tworzenia nowych terapii wspierajacych redukcje stresu wykorzystujacych interakcje człowiek-maszyna. Uczestnicy badania poddani zostali także trzem testom uwagowym: Antysakady, Go/no-go i Stroop, których wyniki wskazały, że grupa poddana GI uzyskała lepsze rezultaty (liczone jako mniejsza liczba błedów w pierwszym i trzecim z wymienionych testów). Przeprowadzone badanie pozwoliło na szersze zrozumienie efektów GI oraz potencjalnych korzyści zwiazanych z regulacja uwagi i funkcjonowaniem poznawczym oraz redukcja stresu, które sa niezbedne we współczesnym świecie charakteryzujacym sie szybkimi i nieustannymi zmianami, mnogościa bodźców i podwyższonym poziomem narażenia na stres.

Contents

1 Introduction

Relaxation techniques have long been studied for their effectiveness in reducing stress and promoting well-being (Carrington et al., 1980; Scotland-Coogan & Davis, 2016; Sung, Roussanov, Nagubandi, & Golden, 2000). In the wake of the COVID-19 pandemic, 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 (Achterberg, 1985; Shafer & Greenfield, 2000).

Guided imagery involves the use of mental imagery to evoke sensory experiences and has gained significant attention as one of the oldest healing resources (Achterberg & Lawlis, 1981). 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 is known to impact multiple physiological systems, such as the 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).

Furthermore, 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 (Perich, Manicavasagar, Mitchell, & Ball, 2013; S. L. Shapiro, 2009; Vøllestad, Nielsen, & Nielsen, 2012; Williams et al., 2014). Previous 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). 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).

2 Overview of the State-of-the-art

2.1 The Benefits of Guided Imagery in Virtual Environments for Relaxation and Well-Being

Numerous approaches, such as relaxation training (Benson, Beary, & Carol, 1974; Bernstein & Borkovec, 1973), biofeedback (Basmajian, 1982), hypnosis (Edmonston Jr, 1977; Barber, Spanos, & Chavez, 1974), and diverse forms of yoga meditation (Morse, Martin, Furst, & Dubin, 1977; D. A. Shapiro & Shapiro, 1982), have proven effective in reducing tension and anxiety. Over the past decade, there has been a surge of interest in mental imagery and its role in promoting health and well-being, including enhancing sports performance (Cooley, Williams, Burns, & Cumming, 2013). Over the past few years, there has been an increasing interest in investigating the effects of meditation and relaxation techniques on attentional control processes. Tang's research (Tang, Lu, Feng, Tang, & Posner, 2015) demonstrated that only five days of mindfulness meditation training improved attentional control in healthy young adults. Similarly, Zeidan (Zeidan, Johnson, Diamond, David, & Goolkasian, 2010) observed that brief mindfulness meditation training improved executive attentional control abilities and reduced anxiety. Furthermore, Ruedy and Schweitzer (Ruedy & Schweitzer, 2010) found that even a brief period of relaxation exercises enhanced participants' ability to resist distractions and maintain focus on a cognitive task. Various literature reviews have also analyzed the impact of meditation on cognitive functions such as attention, memory, and executive control. For example, Chiesa and Serretti (Chiesa & Serretti, 2010) examined the effects of mindfulness meditation on attentional control and found that it resulted in improvements in both selective and sustained attention. Many cognitive psychology and neuroscience studies have investigated the positive effects of mindfulness and meditation training on cognitive functions, utilizing various tasks to assess measures of response accuracy, response time, and associated electrophysiological and neuroimaging patterns, further highlighting the positive impact of mindfulness and meditation on cognitive performance (Malinowski, 2013; Gallant, 2016; Chiesa, Calati, & Serretti, 2011; Cahn & Polich, 2006; Raffone & Srinivasan, 2017; Tang et al., 2015). Alongside the increasing interest in the influence of relaxation techniques on the human mental state, the advancements in neuroimaging technologies provide an even greater potential to merge these two fields. The rapid advancement of technology has led to the development of new tools that offer computer-generated audio-visual displays and immersion in digital 3D environments. The field of research investigating the use of virtual reality (VR) for health and well-being is expanding. A recent study (Wirga & DeBernardi, 2002) aimed to determine whether VR-guided meditation could induce significant changes in EEG waveforms and alleviate pain experienced by patients with cancer. The results showed that EEG recordings can be utilized to investigate neurophysiological changes in brain activity during VR-guided meditation, and demonstrated the potential of VR in pain reduction. Modern brain imaging techniques, such as EEG, are crucial in verifying computational models that aim to understand the relationship between cognition and brain activity (Wójcik, Kawiak, Kwasniewicz, Schneider, & Masiak, 2019).

One promising application of these new technologies is the use of guided imagery to support human well-being. Guided imagery (GI) involves facilitating patients to create vivid and multisensory mental images of positive and pleasant scenarios. It has been observed that GI has significant physiological implications, as the body responds to mental imagery in much the same way as it would to a physical experience (Boucsein & Boucsein, 2012). Notably, guided imagery is among the oldest and most versatile healing practices(Achterberg, 1985). In the late 1970s, health professionals started to report using imagery to influence the course of life-threatening diseases (Pelletier, 1977; Simonton, Matthews-Simonton, & Sparks, 1980). The work of Simonton, an American physician and radiation oncologist, introduced the systematic use of imagery as an adjunct to conventional cancer treatment (H. S. Friedman, 2015; Simonton & Matthews-Simonton, 1981). This approach has been replicated by Fawzy (Fawzy et al., 1993), who arrived at similar conclusions regarding psychotherapeutic intervention in the treatment of patients diagnosed with malignant melanoma. Furthermore, researchers have expanded the study of the effects of imagery on other physiological and psychological correlates, with GI showing promise in reducing psychological stress and smoking behaviors among smokers and ex-smokers (Vines, 1994). Literature also supports the effectiveness of GI in improving health behaviors and reducing psychological distress in the worksite setting (Vines, 1994).

Guided imagery, sometimes referred to as mental imagery or visualization (Kwekkeboom, 2001), is commonly viewed as the mind's language for interpreting inner and outer experiences (Kabat-Zinn, 1990). Achterberg (1985) defined guided imagery as "the thought process that invokes and uses senses: vision, audition, smell, taste. The senses of movement, position, and touch" (Achterberg, 1985) Guided imagery can be facilitated by a guide or self-directed, and some people use guided audio recordings. The practice of guided imagery encompasses the exploration of fantasies, dreams, meditations, drawings, and other creations of the imagination" (Foote, 1996).

The versatility and relevance of guided imagery are broad. For instance, Gruzelier (2001) found that students who used guided imagery during exams were better able to manage stress than those in a control group (Gruzelier, Smith, Nagy, & Henderson, 2001). Singh and Pandey (2007) found that visual imagery helped participants solve more problems (Singh & Pandey, n.d.).

As previously described based on the literature review guided imagery involves using visualization techniques to create a mental image or scenario that promotes relaxation and stress reduction. The immersive nature of VR can enhance the effectiveness of guided imagery (GI) by creating a realistic and engaging environment for the user. For instance, a virtual nature scene can provide a soothing environment for stress reduction or a virtual guided tour of a peaceful location can be used for meditation. These new technologies may have potential applications in a variety of settings, including mental health treatment, pain management, and relaxation therapy. By combining guided imagery with VR and EEG, researchers and practitioners can gain a deeper understanding of the neurological and psychological mechanisms underlying these interventions, and optimize their efficacy for improving human well-being. We can imagine the VR treatment program that was developed with the aim of improving the mental state of oncology patients, as their poor mental state during and after treatment can adversely affect their quality of life and prolong the treatment and recovery processes. By using VR technology, patients can create positive experiences that can help them build positive beliefs and attitudes toward their healing and treatment process. This is particularly beneficial for those who may not have access to specialized psycho-oncological help. However, the integration of VR technology with existing psycho-oncological therapies presents various challenges, including the need to ensure that the relaxation module can respond to changes in the patient's physiological state and breathing pattern. In addition, individuals can vary in their ability to achieve deep relaxation, and future research may investigate the pace at which specific subjects achieve this state. Plotting their state in the function of time would provide valuable information. Machine learning classifiers could aid in classifying biomedical signals towards therapy support. Machine learning tools and algorithms have been used for decades in diagnostics for various disorders such as alcoholism or depression, and advanced modeling of biological systems' behavior, including diagnostic purposes.

2.2 Exploring the Effects of Relaxation Practices on Attention and Alpha Oscillations

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 performance, job performance, and decision-making abilities (Peterson et al., 2017; Arrington, Kulesz, Francis, Fletcher, & Barnes, 2014; Titz & Karbach, 2014; King & Haar, 2017). 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; Gao, Zhao, & Li, 2022). No literature was found on attentional tasks after GI sessions. While the effects of meditation and relaxation techniques on attentional control have been extensively studied, the potential impact of guided imagery (GI) on cognitive performance remains relatively unexplored (Tang et al., 2015; Zeidan et al., 2010; Ruedy & Schweitzer, 2010; Chiesa & Serretti, 2010). However, it is known that other relaxation techniques such as meditation can reduce interference during the Stroop task (Chan & Woollacott, 2007), and meditators have better attentional performance in the Stroop task compared with a meditation-naïve control group (Moore & Malinowski, 2009). High proficiency in this task indicates good attentional control and relatively low automaticity or impulsivity of one's responses (Malinowski, 2013).While studies have shown that meditation practices increase alpha brainwave activity, indicative of relaxed and enhanced mood, little research has examined the electrophysiological effects of GI on cognitive performance (Stapleton et al., 2020; Phneah & Nisar, 2017). The transition from beta to alpha brainwaves during meditation has been associated with higher-level cognitive processes (Hebert, Lehmann, Tan, Travis, & Arenander, 2005; Stapleton et al., 2020). Additionally, executive functions, including inhibition, working memory, and attention shifting, are crucial components of cognitive control (N. P. Friedman & Robbins, 2022; Miyake et al., 2000). Various cognitive tasks, such as anti-saccade, Stroop, and Go/No-Go tasks, have been used to assess executive function and provide insights into its underlying processes (Diamond, 2013; Miyake et al., 2000; Hellmuth et al., 2012; Meule, 2017). 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.

Researchers often choose these attention-based tasks because they offer well-established paradigms for investigating specific attentional processes. These tasks have been extensively studied and validated, allowing for meaningful comparisons across different studies and populations (MacLeod, 1991). By using these tasks, researchers can assess attentional performance, identify underlying cognitive mechanisms, and investigate factors that influence attentional control in various contexts. 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 (Diamond, 2013). While 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 (Miyake et al., 2000; Hellmuth et al., 2012), Stroop tasks assess selective attention and inhibition of irrelevant information, and Go/No-Go tasks assess response inhibition and working memory (Meule, 2017). It was proven that acute psychosocial stress may affect executive action control in a Go/No-Go task (Scholz et al., 2009). Meditation has been found to have a positive impact on attentional processes, influencing various cognitive mechanisms and neural networks. 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) It strengthens the neural pathways involved in attention, including the prefrontal cortex and parietal cortex, which play crucial roles in attentional processing (Lutz, Slagter, Dunne, & Davidson, 2008).Secondly, meditation improves selective attention, allowing individuals to selectively focus on relevant information while filtering out irrelevant stimuli (Jha, Krompinger, & Baime, 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). Furthermore, meditation promotes improved cognitive flexibility, which refers to the ability to switch between different cognitive tasks or mental sets. This enhanced flexibility is associated with changes in the anterior cingulate cortex and the executive control network, allowing individuals to adaptively shift their attention and cognitive resources as needed (Malinowski, 2013). 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 networks are responsible for regulating attentional processes. Meditation has been shown to increase alertness, enhance the ability to shift attention, and improve executive control functions (Tang, Posner, & Rothbart, 2014). These changes result in more efficient allocation of attentional resources and better performance in attention-demanding tasks. It was decided to explore Guided Imagery as the relaxation method, because in opposite to meditation Guided imagery 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.

3 Research description and hypothesis

3.1 Research description

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 (2020), 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 participants were screened for chronic medical conditions and were asked to disclose any such conditions, including mental disorders, during the screening process. Individuals with chronic diseases, including but not limited to chronic fatigue syndrome, cancer, and mental disorders, were excluded from the study. The experimental cohort was then randomly divided into two sub-cohorts: Sub-cohort A, which consisted of 30 subjects exposed to relaxation, and Sub-cohort B, which consisted of 30 subjects assigned to perform the mental task. After undergoing pre-processing and eliminating data with poor quality, only participants who provided complete and good EEG recordings while meeting all exclusion criteria were included in the final analysis. This resulted in a GI sub-cohort of 20 subjects and a mental task-engaged sub-cohort of 28 subjects. The participants in this research were male computer science students between the ages of 17-24 from a Computer Science department at Maria Curie-Sklodowska University in Lublin, Poland. They were required to have short hair and be right-handed, and all participants were of Polish nationality or citizenship and fluently spoke Polish. Males were selected for the study due to the preponderance of male students in the department, as well as documented gender differences in electroencephalogram patterns (Wada, Takizawa, Zheng-Yan, & Yamaguchi, 1994; Cantillo-Negrete et al., 2017) Additionally, participants had to be 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. They were also required to be nonsmokers and were asked not to consume alcohol or any medications at least 72 hours before participation in the experiment. 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. EEG recordings were obtained using a 256-channel dense-array EEG amplifier with a HydroCel GSN 130 manufactured by Electrical Geodesic Systems (EGI) with a sampling frequency of 250 Hz. Net Station 4.5.4 and SmartEye 5.9.7 software were used for artifact removal and gaze calibration, respectively. The laboratory was also equipped with a geodesic photogrammetry system (GPS), which was operated using Net Local 1.00.00 and GeoSource 2.0. ERP experiments were designed in PST e-Prime 2.0.8.90. Additionally 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. & Sedek, G. 2020 unpublished research materials from SWPS University of Social Sciences and Humanities. The Scale of Helplessness of Contracting an Infectious Disease was based on previous research on uncontrollability in the classroom, known as the Intellectual Helplessness Scale (Rydzewska, Rusanowska, Krejtz, & Sedek, 2017). The latter focuses on situations where individuals try to solve a task without understanding it for an extended period, leading to intellectual helpless-

ness in that task domain. The researchers adapted this scale to the context of the COVID-19 pandemic, where individuals may experience feelings of helplessness and anxiety due to the uncontrollable situation. The first rappidly growing state of this pandemic was analyzed by Koczkodaj et al. (W. Koczkodaj et al., 2020). 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 the respondent generally feels, 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 primary indicator in this task is the average percentage of correct responses for the anti-saccade 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. The test measures the ability to suppress automatic responses (response inhibition) and focus attention on the task at hand (Huang et al., 2019).

The task is 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 conflict-triggering 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 main indicator in this test is the average percentage of correct answers. Additional indicators, including reaction times for congruent and incongruent trials. The magnitude of the difference in response times between congruent and incongruent trials is a measure of interference control.

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 pseudorandomized order while following the rule that No-go trials were preceded by 2 or 5 Go trials. The main block of trials was preceded by 10 practice trials, consisting of 2 No-go and 8 Go trials. As a primary measure of Go/No-go task performance - attention control was the percentage of correct responses for Go trials after No-go trials. Additional measures included reaction time for Go trials, as well as the mean percentage of correct responses for both Go and 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 or scene. 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. 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

3.2 Research hypothesis

The primary research hypothesis of this study posits that a brief GI session can lower stress levels in healthy male individuals who lack prior exposure to such sessions or have a history of chronic health issues. To test this hypothesis, a cohort of 30 participants underwent a GI session, during which beta power reductions and alpha state increases were monitored using EEG equipment, and self-reported questionnaires were used to assess the session's efficacy in reducing stress. This study also aims to demonstrate the feasibility of utilizing a general linear model (GLM) for accurately differentiating between different mental states based on EEG signal analysis. While the GLM is a well-established classifier, its implementation in EEG signal analysis is relatively unexplored. The novelty of this research lies in its ability to showcase the potential of EEG signal classification with a 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.

In addition to assessing the effectiveness of the GI session, the study aimed to examine whether the outcomes of attentional tasks (Stroop, Go/No-Go, and Anti-Saccades tests) can differentiate between the group of participants who received the GI intervention and other groups of 30 randomly selected male participants who completed a mental task. Specifically, we compared the number of errors committed on these tasks between the two groups. Based on the Hudetz study (Hudetz et al., 2000) after the relaxation session using guided imagery, participants showed a significant improvement in working-memory scores compared to the music and control groups. The findings support the hypothesis that guided imagery enhances working-memory performance and suggest that relaxation techniques positively influence human information processing, thus, it is expected that engaging in a guided imagery session will lead to improvements in attentional control processes. 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) and 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 (Keith, Blackwood, Mathew, & Lecci, 2017; Brown & Ryan, 2003; Feldman, Hayes, Kumar, Greeson, & Laurenceau, 2007; Mrazek, Mooneyham, & Schooler, 2014; Moore & Malinowski, 2009; 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 reducing stress levels, guided imagery may alleviate distractions and promote a state of focused attention. Secondly, the visualization and mental imagery involved in guided imagery exercises can enhance cognitive flexibility and cognitive resource allocation. Engaging in vivid sensory experiences during guided imagery may train the brain to better allocate attentional resources, filter out irrelevant information, and maintain cognitive flexibility, which are crucial components of attentional control. Lastly, guided imagery may modulate neural activity, including changes in alpha power, which has been associated with improved attentional control and cognitive performance. Previous studies have shown that increases in alpha power are correlated with enhanced attentional processes, including selective attention and inhibition of distracting stimuli.

Finally, we hypothesized that modifications in alpha power may mediate the association between the employment of GI and the reduction in errors on the attention tests. To test this hypothesis, we undertook a mediation analysis to investigate the potential relationship between these variables.

3.3 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 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 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.

4 Research results

This study has several notable findings that contribute to the novelty and significance of the research. Firstly, the analysis of brainwave data during guided imagery (GI) sessions revealed a significant increase in alpha power, indicating a state of deep relaxation. This finding supports the hypothesis that GI can induce relaxation and promote a relaxed mental state. 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.

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. 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 practical implications of this research are noteworthy. The findings support the potential application of GI as an effective intervention for stress reduction and relaxation. The study's results highlight the positive impact of GI on attentional control abilities, which can be beneficial in stress-inducing contexts. The incorporation of GI in stress management protocols and its potential role in optimizing cognitive performance provide valuable insights for therapists and practitioners. Moreover, the study opens up possibilities for the

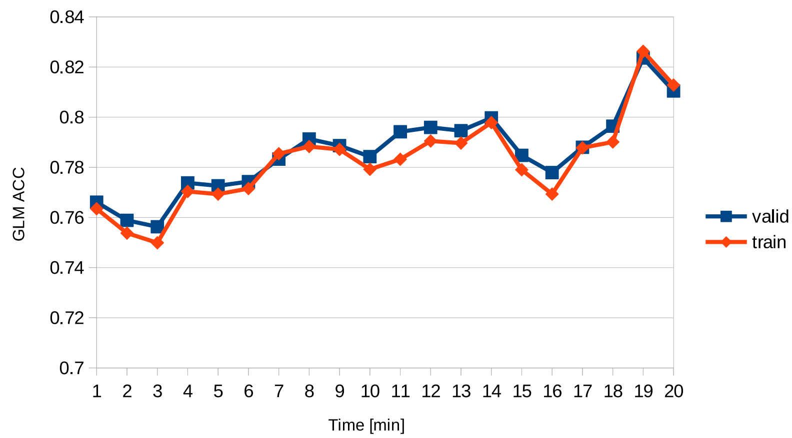

Figure 1: The 14th minute choice justification (Zemla et al., 2023)

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.

The study's findings on the relationship between various cognitive and emotional measures, including brain wave activity, stress reduction, attentional control, and emotional well-being, provide important insights into the complex interplay between these variables. These findings could inform the development of more holistic and integrated interventions that target multiple aspects of cognitive and emotional functioning simultaneously.

Table 1 presented in Fig. 2 shows the participants' characteristics for subjective measures in a study with two groups: GI Group (N=20) and Mental Task Group (N=28). The measures include anxiety, helplessness, stress reduction, and relaxation increase. One-way analysis of variance (ANOVA) was conducted to test for significant differences between the groups.

Table 2 presented in Fig. 3 presents the results of a study that compared two different interventions, GI and mental tasks, on brain wave patterns and attentional control measures.

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

Figure 2: (Zemla et al., 2023)

Table 2. Participants' characteristics for brain waves and attentional control 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
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.

Figure 3: (Zemla et al., 2023)

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** **	-

Figure 4: (Zemla et al., 2023)

Pearson's R correlations were conducted to examine the relationships between different variables. Table 3 presented in Fig. 4 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. Additionally, higher levels of Stress Reduction were associated with lower levels of Helplessness, while higher anxiety levels were associated with poorer performance on attentional control tasks. Interestingly, higher anxiety levels were also associated with lower Alpha Power at the 14th minute. These findings underscore the need for further research to understand the complex interplay between brain wave activity, attentional control, stress reduction, helplessness, and anxiety, and their potential implications for cognitive functioning and mental health.

Significant correlations were identified between various variables, including brain wave activity, attentional control measures, stress reduction, helplessness, and anxiety, suggesting that these variables are interrelated and may have important implications for cognitive functioning and emotional well-being. The

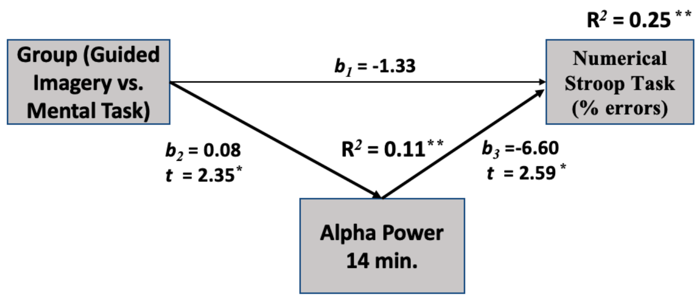

Figure 5: The effect of GI on reducing erroneous reactions in the Stroop test is mediated by Alpha Power at 14 minutes (Zemla et al., 2023)

study's findings provide valuable insight into the potential benefits of GI as an intervention for improving cognitive performance and emotional well-being and may inform the development of effective interventions aimed at enhancing cognitive and emotional functioning. Furthermore, the study's unique aspect is utilizing multi-sensor EEG signal classification and a GLM to classify two mental states, providing evidence of the possibility of constructing new Human-Machine Interaction therapies.

The study also employed mediation models to investigate the relationship between GI, alpha power, and cognitive performance, which provided a comprehensive understanding of the interplay between these variables. The mediational models shed light on the potential mechanisms through which GI can affect cognitive performance and underscore the necessity for additional investigations to gain a deeper understanding of this domain.

The mediation model presented in Figure 5 provides evidence that the relationship between guided imagery (GI) and performance on the Stroop test is mediated by alpha power in the 14th minute. Specifically, the negative coefficient between GI and the Stroop test indicates that engaging in GI is associated with better performance on the Stroop test, and alpha power serves as a reliable mediator in this relationship.

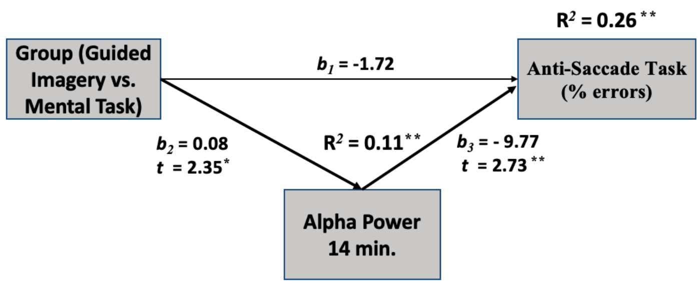

Figure 6: The effect of GI on reducing erroneous reactions in the Anti-Saccade test is mediated by Alpha Power at 14 minutes (Zemla et al., 2023)

Furthermore, the mediation analysis depicted in Figure 6 suggests that changes in alpha power partially explain the relationship between GI and errors in the Anti-saccade test. The analysis indicates that an increase in alpha power is linked to a reduction in errors in the Anti-saccade test.

The significance of the t-values provides support for the relationships depicted in the mediation model, suggesting that the observed coefficients are unlikely to have occurred by chance. These results indicate that the use of GI has the potential to enhance cognitive performance, particularly in tasks requiring inhibitory control, by promoting increased alpha power. Nevertheless, further research is necessary to validate these findings and delve into the underlying mechanisms of this relationship. 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. It also underscores the need for further research in this area to fully explore the possibilities and limitations of these innovative approaches. Future research directions are suggested based on the study's findings. The individual pace at which participants enter a deep state of relaxation during GI sessions should be investigated, as personal characteristics and external influences can affect the timing. Plotting the state as a function of time would provide valuable insights into the dynamics of relaxation induction. Additionally, the study's results offer possibilities for further investigations into the characteristics of the deep state of relaxation inclination in relation to psychological personality predictors.

In conclusion, this study contributes novel findings by examining brainwave changes during GI, the effectiveness of machine learning classifiers in classifying brain states, and the cognitive benefits of GI on attentional control. The research sheds light on the potential advantages of GI as an intervention for enhancing cognitive performance and emotional well-being. These findings suggest that GI can enhance attentional control and cognitive flexibility, providing a cognitive benefit compared to traditional mindfulness practices. The findings have implications for stress management, therapy support, and the development of innovative human-machine interaction technologies. 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.

5 Conclusion and Future Directions

The researchers' hypotheses were supported by the findings, as the GI intervention resulted in increased alpha power and improved performance on attentional tests, particularly the Stroop and Anti-saccade tests. The lack of significant improvement in the Go/No-Go test can be attributed to differences in attentional demands across the various tests, each measuring a specific type of attentional control. GI, unlike mindfulness practices, does not enhance focused attention but involves visualizing pleasant images that have a stress-reducing and anxiety-reducing effect, impacting alpha power. Alpha power has been found to be positively correlated with information processing speed.

The study's mediational model sheds light on the relationship between GI, alpha power at the 14th minute, and performance on attentional control tasks. It provides a comprehensive understanding of the interplay between these variables and offers insights into the potential mechanisms through which GI affects cognitive performance, particularly in the context of attentional control tasks. Further investigations are warranted to gain a deeper understanding of this domain, and pairwise comparisons methods can be considered for analysis accuracy.

In conclusion, this study provides valuable insights into the potential benefits of GI as an intervention for improving cognitive performance and emotional well-being. The findings contribute to the existing literature on cognitive and emotional interventions and have implications for the development of effective interventions aimed at enhancing cognitive and emotional functioning. Future research could explore the long-term effects of GI interventions and further investigate the relationships between cognitive and emotional measures. Additionally, the study's utilization of multi-sensor EEG signal classification and a GLM highlights the possibility of developing new Human-Machine Interaction therapies. Guided imagery (GI) differs from mindfulness practices in that it does not primarily focus on enhancing focused attention but rather involves the visualization of pleasant images, which can induce stress reduction and anxiety reduction responses, potentially influencing alpha power. It is worth noting that other research has shown a positive correlation between alpha power and information processing speed (Rathee, Bhatia, Punia, & Singh, 2020). The findings of the study suggest that the GI intervention may have had a more prominent impact on cognitive flexibility, which could have contributed to improved performance on the Stroop and Anti-saccade tasks. These results emphasize the cognitive mechanisms involved in the GI intervention and its potential to enhance cognitive flexibility in a manner that is different from traditional mindfulness practices.

The mediational model used in this study provides a comprehensive understanding of the interplay among GI, alpha power in the 14th minute, and performance on the Stroop and Anti-saccade tests. It sheds light on the potential mechanisms through which GI can influence cognitive performance, particularly in the context of attentional control tasks. In conclusion, the mediational model presented here offers a valuable framework for comprehending the complex associations between GI, alpha power, and cognitive performance. It highlights the need for further investigations to deepen our understanding in this area. Specifically, the consideration of pairwise comparison methods, such as those analyzed for accuracy by Koczkodaj (W. W. Koczkodaj, 1996), can be beneficial.

In addition, the study explored the application of machine learning techniques to classify brain states during relaxation and mental tasks. The results demonstrated the feasibility of accurately distinguishing between deep relaxation and mental tasks using classifiers. 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. The study also discussed potential applications of machine learning classifiers in therapy support, brain-computer interfaces (BCIs), and AI-trained robotic therapists.

The conclusions from these two aspects of the study are mutually supportive. The findings suggest that GI can effectively improve cognitive performance and emotional well-being by enhancing alpha power and attentional control. Furthermore, machine learning classifiers provide a reliable means of classifying brain states during relaxation, with longer or more signal input leading to 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. 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.

6 Contribution to the science

This study aims to fill a significant research gap by investigating the quantitative modeling of brainwave activities during guided imagery. What sets this study apart from previous research is its focus on exploring brainwave patterns associated with guided imagery relaxation, specifically the increase in alpha power and reduction in beta power, which indicate a state of relaxation. These patterns stand in contrast to existing studies that have predominantly examined brainwave changes during stress, where alpha power decreases and beta power increases (Rees, 1995; Thomas & Sethares, 2010). The novelty of this research lies in its exploration of brainwave activity during guided imagery, shedding light on the neural mechanisms underlying this relaxation technique.

To achieve this, 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 an innovative approach to understanding and differentiating brain states associated with guided imagery and mental workload. This novel 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.

The application of EEG signal analysis and GLM classifiers in the context of guided imagery research represents a significant advancement in the field. It allows researchers to delve deeper into the intricacies of brainwave activity during guided imagery and explore the potential correlations with relaxation and cognitive processes. By capturing and analyzing brainwave data, this study offers valuable insights into the underlying neural mechanisms of guided imagery, contributing to the growing body of knowledge on the efficacy of this relaxation technique.

Furthermore, this research has practical implications for the development of computer-based interventions aimed at 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. This innovative approach has the potential to revolutionize the field of mental health by providing accessible and effective tools for anxiety and stress management.

Additionally, the study expands on previous research that has examined the effects of relaxation techniques on attention and executive functions. While studies have 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 aims to shed light on the impact of GI on cognitive inhibition, selective attention, and response inhibition.

In summary, this study's novelty lies in its exploration of brainwave patterns during guided imagery relaxation, offering a fresh perspective on the neural mechanisms underlying this relaxation technique. By employing EEG signal analysis and GLM classifiers, this research aims to accurately classify and model brain states associated with guided imagery and mental workload. The findings have the potential to pave the way for the development of therapy-oriented brain-computer interfaces, contributing to anxiety and stress reduction through computer-based interventions. This study represents a significant advancement in the field, bridging the research gap and expanding our understanding of the impact of guided imagery on brainwave activity and relaxation plus this research contributes to the field by uncovering the potential benefits of GI in improving attentional control and executive functions, and it paves the way for future studies on the development of therapy-oriented interventions for anxiety and stress reduction.

7 A chapter and articles comprising the thesis

7.1 Investigating the lnfluence of Guided lmagery Relaxation on the Selected Electrophysiologic'al Parameters of Human Body

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

Katarzyna Zemła*
Grzegorz M. Wojcik
Filip Postępski
Łukasz Kwaśniewicz
Andrzej Kawiak

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

*Corresponding author — kzemla1@st.swps.edu.pl

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.

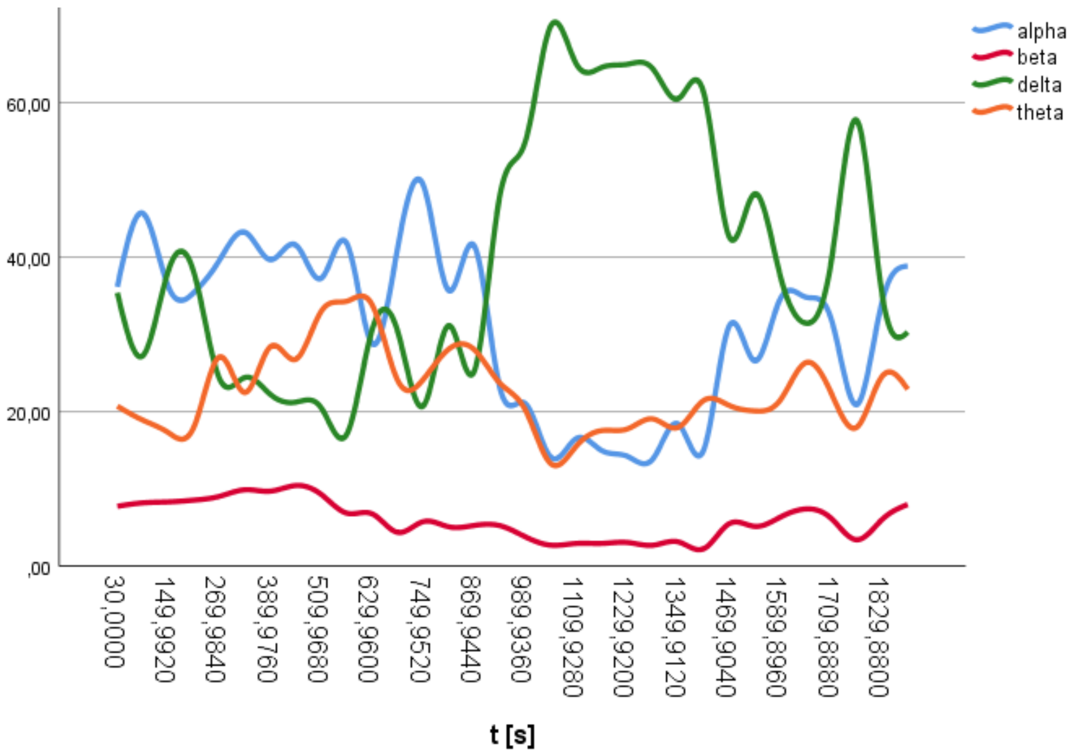

Figure 2: Percentage of each wave during the experiment

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

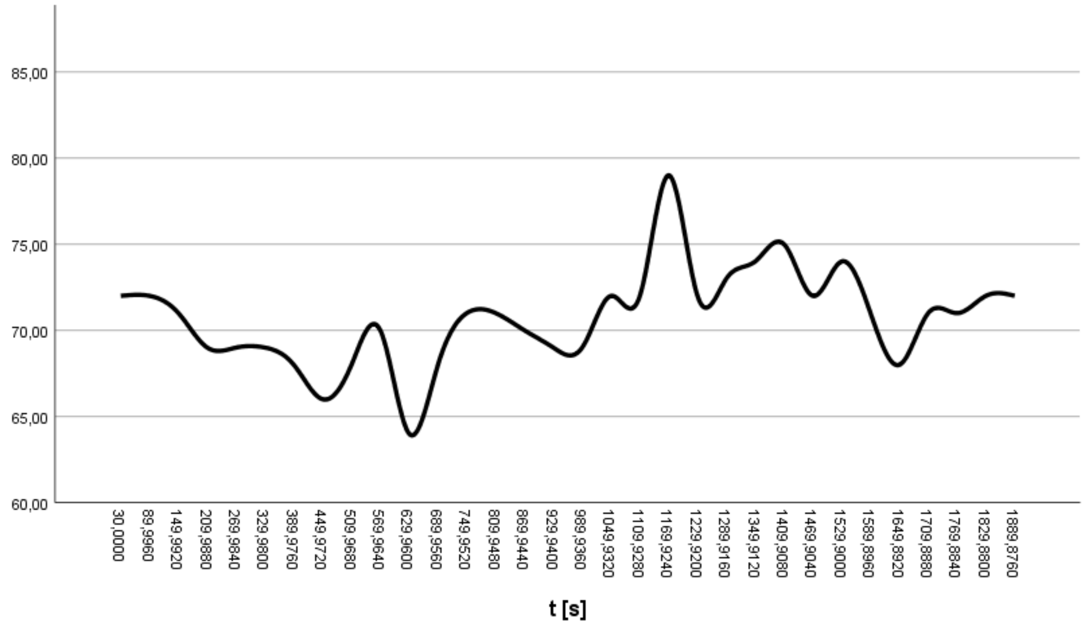

Figure 3: Pulse variations during the experiment

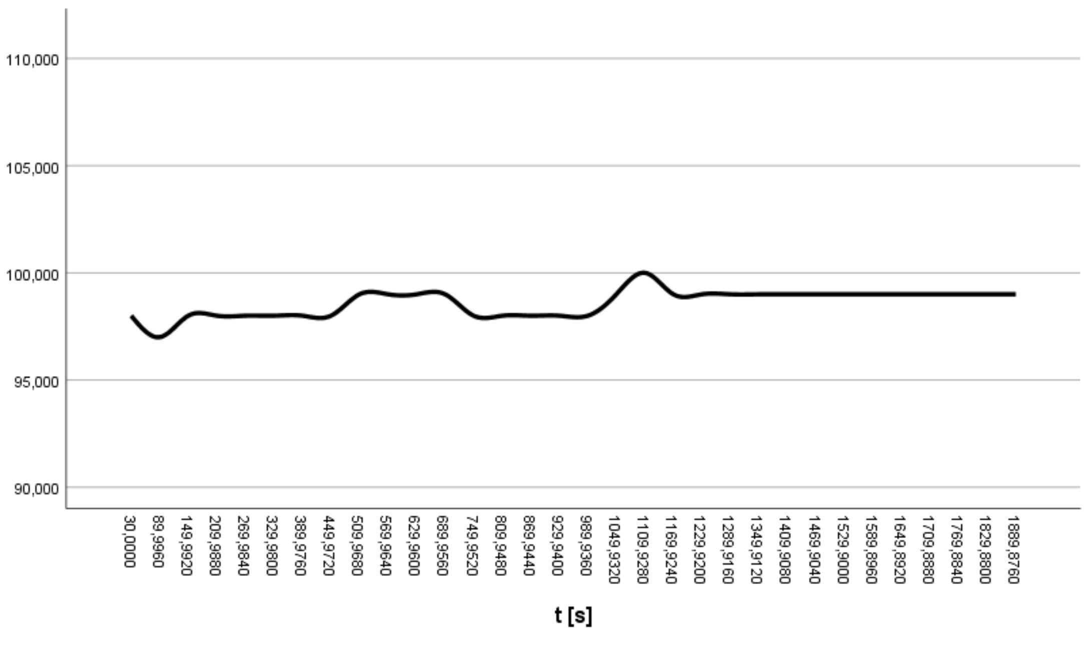

Figure 4: Hemoglobin saturation level (SpO2) during the experiment

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.

References

[1] JE Auerbach, TD Oleson, and GF Solomon. Biofeedback, guided imagery, and hypnosis as an adjunctive treatment for aids and aids-related complex. In *Proceedings o f the Third National Conference on the Psychology of Health,*

Immunity, and Disease in Storrs, CT: The National Institute for the Clinical Application of Behavioral Medicine, volume 50, 1992.

[2] Gary G Berntson, John T Cacioppo, and Karen S Quigley. Respiratory sinus arrhythmia: autonomic origins, physiological mechanisms, and psychophysiological implications. *Psychophysiology*, 30(2):183–196, 1993.

[3] Wolfram Boucsein. *Electrodermal activity*. Springer Science & Business Media, 2012.

[4] P Bušek and D Kemlink. The influence of the respiratory cycle on the eeg. *Physiol Res*, 54:327–33, 2005.

[5] Bruce M Cappo and David S Holmes. The utility of prolonged respiratory exhalation for reducing physiological and psychological arousal in non-threatening and threatening situations. *Journal of psychosomatic research*, 28(4):265–273, 1984.

[6] Gianfranco Cervellin and Giuseppe Lippi. From music-beat to heart-beat: a journey in the complex interactions between music, brain and heart. *European journal of internal medicine*, 22(4):371–374, 2011.

[7] K Davies. Search and deploy. bio–it world, october 16, 2006, 2006.

[8] Fawzy I Fawzy, Nancy W Fawzy, Christine S Hyun, Robert Elashoff, Donald Guthrie, John L Fahey, and Donald L Morton. Malignant melanoma: Effects of an early structured psychiatric intervention, coping, and affective state on recurrence and survival 6 years later. *Archives of general psychiatry*, 50(9):681–689, 1993.

[9] Howard S Friedman. *Encyclopedia of mental health*. Academic Press, 2015.

[10] Sarnik Gaurav, Sinha Meenakshi, Ghate Jayshri, and Sinha Ramanjan. Effect of alterations in breathing patterns on eeg activity in normal human subjects. *Int J Curr Res Med Sci*, 2:38–45, 2016.

[11] John H Gruzelier, Trevor Thompson, Emma Redding, Rosemary Brandt, and Tony Steffert. Application of alpha/theta neurofeedback and heart rate variability training to young contemporary dancers: State anxiety and creativity. *International Journal of Psychophysiology*, 93(1):105–111, 2014.

[12] Erwin Roy John, LS Prichep, J Fridman, and P Easton. Neurometrics: computer-assisted differential diagnosis of brain dysfunctions. *Science*, 239(4836):162–169, 1988.

[13] Aleksandra Kawala-Sterniuk, Michal Podpora, Mariusz Pelc, Monika Blaszczyszyn, Edward Jacek Gorzelanczyk, Radek Martinek, and Stepan Ozana. Comparison of smoothing filters in analysis of eeg data for the medical diagnostics purposes. *Sensors*, 20(3):807, 2020.

[14] PJ Kelly. Evaluation of a meditation and hypnosis-based stress management program for men with hiv. In *Poster presented at the Fifth International Conference on AIDS, Montreal*, 1989.

[15] Glenn E Knowlton and Kevin T Larkin. The influence of voice volume, pitch, and speech rate on progressive relaxation training: application of methods from speech pathology and audiology. *Applied psychophysiology and biofeedback*, 31(2):173–185, 2006.

[16] Stefan Koelsch and Lutz Jäncke. Music and the heart. *European heart journal*, 36(44):3043–3049, 2015.

[17] Margaret McCoy Lynch. Factors influencing successful psychotherapy outcomes. *Master of Social Work Clinical Research Papers*, 2012.

[18] Monica McHenry, Patricia A Parker, Walter F Baile, and Renato Lenzi. Voice analysis during bad news discussion in oncology: reduced pitch, decreased speaking rate, and nonverbal communication of empathy. *Supportive Care in Cancer*, 20(5):1073–1078, 2012.

[19] P Newton and L Marx. *The Clinical Use of Hypnotic Imagery in HIV Positive Men.* The Center, 1990.

[20] Thanh Nhan Nguyen, Stefan Nilsson, Anna-Lena Hellström, and Ann Bengtson. Music therapy to reduce pain and anxiety in children with cancer undergoing lumbar puncture: a randomized clinical trial. *Journal of Pediatric Oncology Nursing*, 27(3):146–155, 2010.

[21] Burkhard Peter. Hipnoza i psychoterapia pacjentów z hiv, arc i aids. hypnosis and psychotherapy with hiv, arc and aids patients. *Psychiatria polska*, 1(23), 2005.

[22] JT Ptacek and Tara L Eberhardt. Breaking bad news: a review of the literature. *Jama*, 276(6):496–502, 1996.

[23] A Ramírez-Carrasco, C Butrón-Téllez Girón, O Sanchez-Armass, and M Pierdant-Pérez. Effectiveness of hypnosis in combination with conventional techniques of behavior management in anxiety/pain reduction during dental anesthetic infiltration. *Pain Research and Management*, 2017, 2017.

[24] Ernest Lawrence Rossi. *The Breakout Heuristic: The New Neuroscience of Mirror Neurons, Consciousness, and Creativity in Human Relationships.* Milton H. Erickson Foundation Press, 2007.

[25] Marc A Russo, Danielle M Santarelli, and Dean O'Rourke. The physiological effects of slow breathing in the healthy human. *Breathe*, 13(4):298–309, 2017.

[26] Victor L Ryan and James A Moses. Therapist warmth and status in the systematic desensitization of test anxiety. *Psychotherapy: Theory, Research & Practice*, 16(2):178, 1979.

[27] Nilima Salankar, Saeed Mian Qaisar, Paweł Pławiak, Ryszard Tadeusiewicz, and Mohamed Hammad. Eeg based alcoholism detection by oscillatory modes decomposition second order difference plots and machine learning. *Biocybernetics and Biomedical Engineering*, 2022.

[28] Klaus R Scherer, Tom Johnstone, and Gundrun Klasmeyer. *Vocal expression of emotion.* Oxford University Press, 2003.

[29] O Carl Simonton and STEPHANIE MATTHEWS-SIMONTON. Cancer and stress counselling the cancer patient. *Medical Journal of Australia*, 1(13):679–683, 1981.

[30] O Carl Simonton, Stephanie Matthews-Simonton, and T Flint Sparks. Psychological intervention in the treatment of cancer. *Psychosomatics*, 21(3):226–233, 1980.

[31] Jonathan C Smith. *Relaxation, meditation, & mindfulness: A mental health practitioner's guide to new and traditional approaches.* Springer Publishing Company, 2005.

[32] Mohammad Soleymani, Sadjad Asghari-Esfeden, Maja Pantic, and Yun Fu. Continuous emotion detection using eeg signals and facial expressions. In *2014 IEEE International Conference on Multimedia and Expo (ICME)*, pages 1–6. IEEE, 2014.

[33] David Spiegel, HelenaC Kraemer, JoanR Bloom, and Ellen Gottheil. Effect of psychosocial treatment on survival of patients with metastatic breast cancer. *The lancet*, 334(8668):888–891, 1989.

[34] E Szeląg. Nowe tendencje w terapii logopedycznej w świetle badań nad mózgiem,[w:] podstawy neurologopedii. *Podręcznik akademicki, red. T. Gałkowski, G. Jastrzębowska, E. Szeląg, Opole*, pages 1028–1048, 2005.

[35] Ryszard Tadeusiewicz. Neural networks as a tool for modeling of biological systems. *Bio-Algorithms and Med-Systems*, 11(3):135–144, 2015.

[36] Michal Teplan, Anna Krakovská, and Marián Špajdel. Spectral eeg features of a short psycho-physiological relaxation. *Measurement Science Review*, 14(4):237–242, 2014.

[37] Frederick Travis. Autonomic and eeg patterns distinguish transcending from other experiences during transcendental meditation practice. *International Journal of psychophysiology*, 42(1):1–9, 2001.

[38] Julian Treasure. *Sound business.* Management Books 2000 Limited, 2011.

[39] Ilse Van Diest, Karen Verstappen, André E Aubert, Devy Widjaja, Debora Vansteenwegen, and Elke Vlemincx. Inhalation/exhalation ratio modulates the effect of slow breathing on heart rate variability and relaxation. *Applied psychophysiology and biofeedback*, 39(3-4):171–180, 2014.

[40] Elke Vlemincx, Ilse Van Diest, Steven De Peuter, and Omer Van den Bergh. Relaxatie: een 'cold case'hervat. *Psychologie en Gezondheid, jaargang 2007*, 35(1):14–23, 2007.

[41] Kristin M Voegtline, Kathleen A Costigan, Heather A Pater, and Janet A DiPietro. Near-term fetal response to maternal spoken voice. *Infant Behavior and Development*, 36(4):526–533, 2013.

[42] PM West, EM Blumberg, and FW Ellis. An observed correlation between psychological factors and growth rate of cancer in man. In *Cancer Research*, volume 12, pages 306–307. AMER ASSOC CANCER RESEARCH PO BOX 11806, BIRMINGHAM, AL 35202, 1952.

[43] Mariusz Wirga and Michael DeBernardi. The abcs of cognition, emotion, and action. *Archives of Psychiatry and Psychotherapy*, 4(1):5–16, 2002.

[44] Grzegorz M Wójcik, Andrzej Kawiak, Lukasz Kwasniewicz, Piotr Schneider, and Jolanta Masiak. Azure machine learning tools efficiency in the electroencephalographic signal p300 standard and target responses classification. *Bio-Algorithms and Med-Systems*, 15(3), 2019.

[45] Grzegorz Marcin Wojcik, Joalnta Masiak, Andrzej Kawiak, Lukasz Kwasniewicz, Piotr Schneider, Nikodem Polak, and Anna Gajos-Balinska. Mapping the human brain in frequency band analysis of brain cortex electroencephalographic activity for selected psychiatric disorders. *Frontiers in Neuroinformatics*, 12:73, 2018.

[46] Grzegorz Marcin Wójcik, Joalnta Masiak, Andrzej Kawiak, Piotr Schneider, Lukasz Kwasniewicz, Nikodem Polak, and Anna Gajos-Balinska. New protocol for quantitative analysis of brain cortex electroencephalographic activity in patients with psychiatric disorders. *Frontiers in Neuroinformatics*, 12:27, 2018.

[47] Grzegorz Marcin Wójcik, Jolanta Masiak, Andrzej Tadeusz Kawiak, Lukasz Kamil Kwasniewicz, Piotr Schneider, Filip Postepski, and Anna Gajos-Balinska. Analysis of decision-making process using methods of quantitative electroencephalography and machine learning tools. *Frontiers in Neuroinformatics*, 13:73, 2019.

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

applied sciences

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]

[1] Institute of Psychology, SWPS University of Social Sciences and Humanities, 03-815 Warsaw, Poland
[2] Department of Neuroinformatics and Biomedical Engineering, Institute of Computer Science, Maria Curie-Sklodowska University, 20-033 Lublin, Poland
* Correspondence: gmwojcik@live.umcs.edu.pl; Tel.:+48-81-537-29-40

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

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

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.

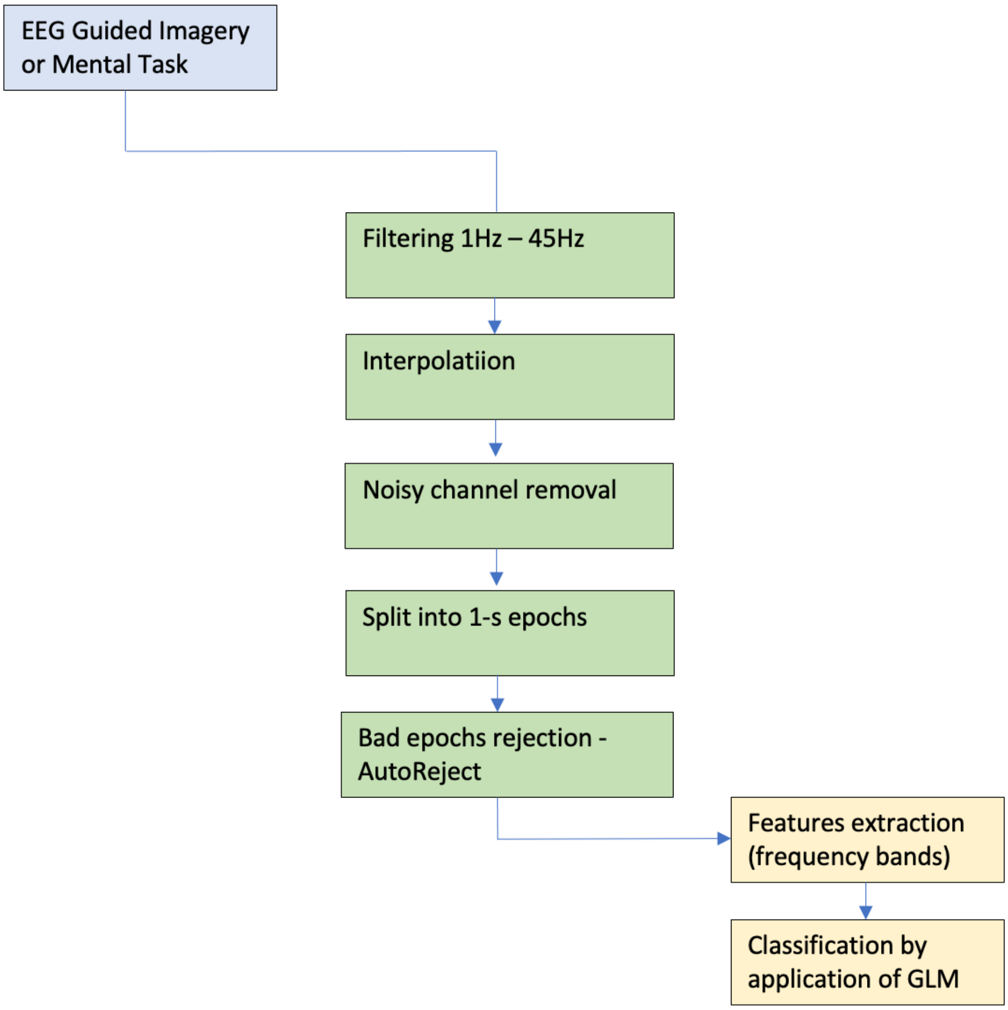

Figure 1. Data analysis pipeline for the experiments. For details, see the text.

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.

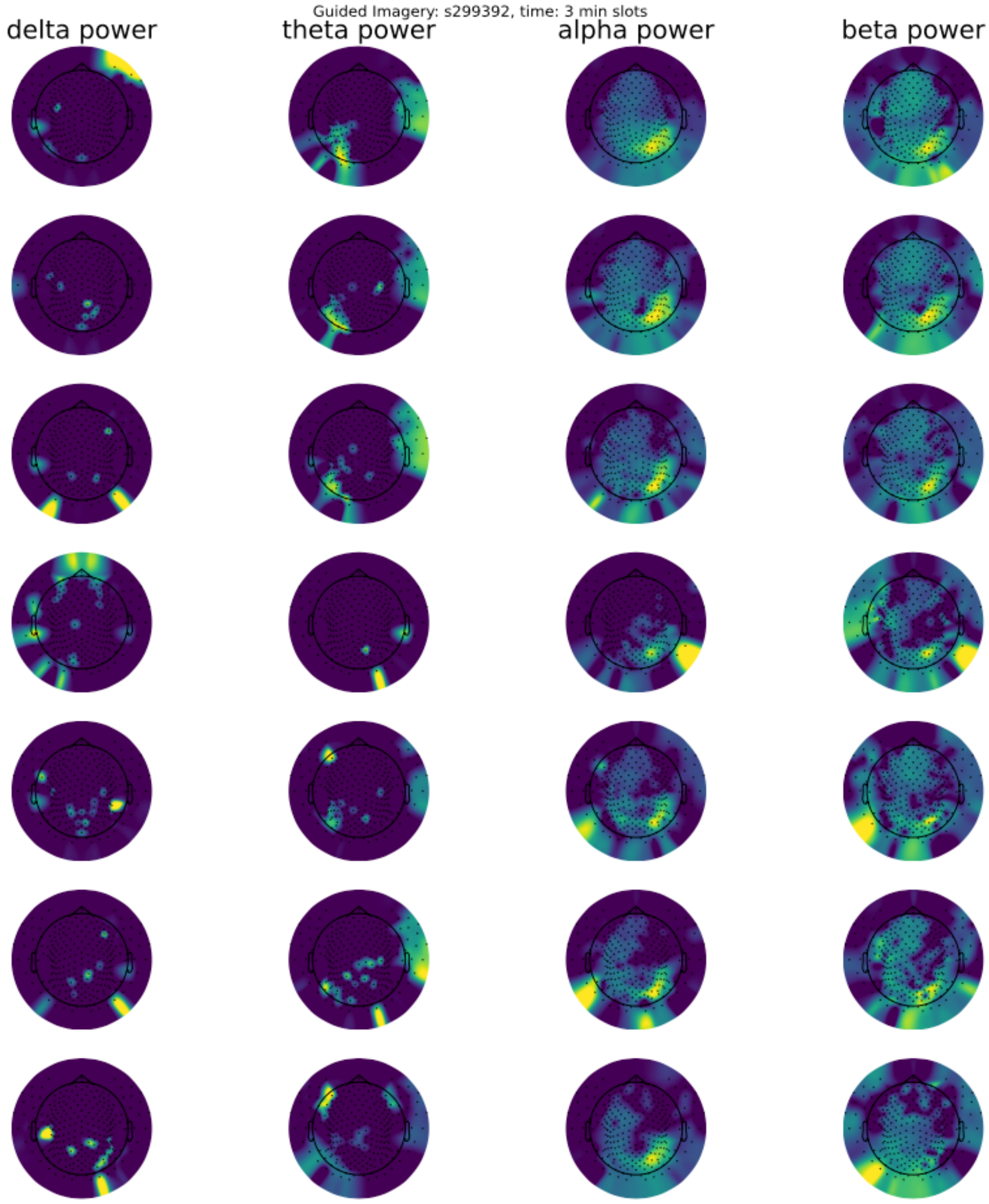

Figure 2. Power activity in the δ, θ, α, and β bands for participant s299392 exposed to guided imagery. Each row, one-by-one, represents a 3-min slot, for 21-min in total. For details, see the text.

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.

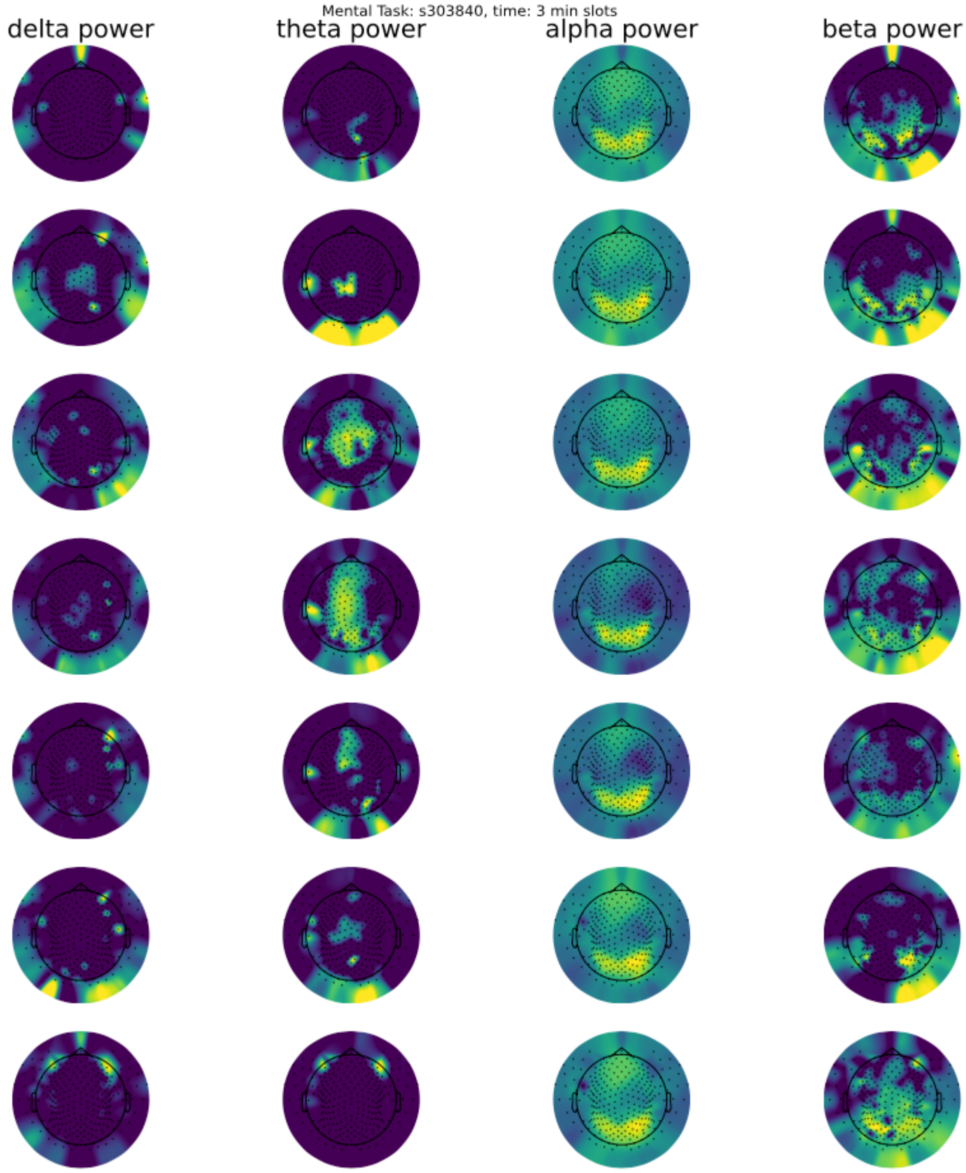

Figure 3. Power activity in the δ, θ, α, and β bands for participant s303840 exposed to mental task. Each row, one-by-one, represents a 3-min slot, for 21-min in total. For details, see the text.

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

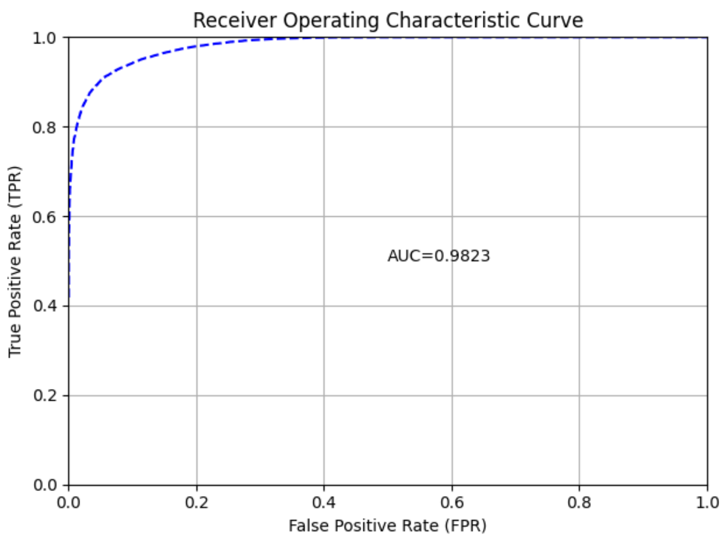

Figure 4. The ROC curve for the results presented in Table 3.

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.

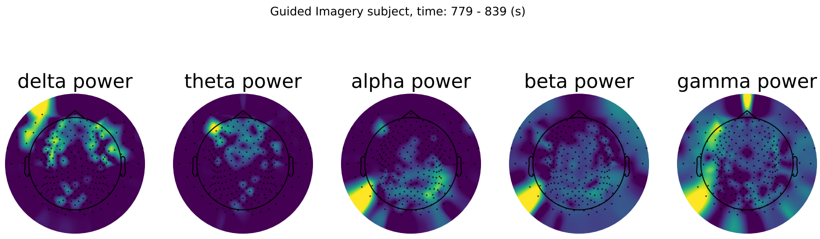

Figure 5. Power activity in the δ, θ, α, and β bands for participant s299392 exposed to guided imagery.

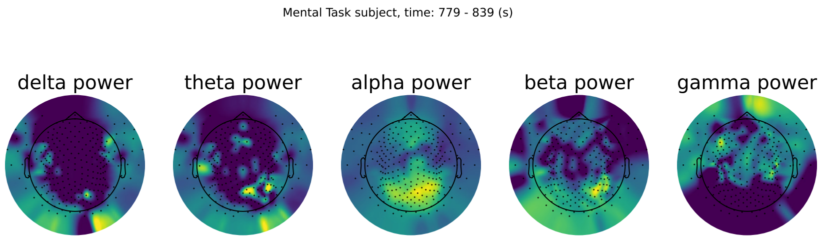

Figure 6. Power activity in the δ, θ, α, and β bands for participant s303840 exposed to the mental task.

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.

References

1. Carrington, P.; Collings, G.H., Jr.; Benson, H.; Robinson, H.; Wood, L.W.; Lehrer, P.M.; Woolfolk, R.L.; Cole, J.W. The use of meditation–relaxation techniques for the management of stress in a working population. *J. Occup. Med. Off. Publ. Ind. Med. Assoc.* **1980**, *22*, 221–231.
2. Scotland-Coogan, D.; Davis, E. Relaxation techniques for trauma. *J.-Evid.-Inf. Soc. Work* **2016**, *13*, 434–441. [CrossRef] [PubMed]
3. Sung, B.; Roussanov, O.; Nagubandi, M.; Golden, L. A002: Effectiveness of various relaxation techniques in lowering blood pressure associated with mental stress. *Am. J. Hypertens.* **2000**, *13*, 185A. [CrossRef]
4. Mamun, M.A. Suicide and suicidal behaviors in the context of COVID-19 pandemic in Bangladesh: A systematic review. *Psychol. Res. Behav. Manag.* **2021**, *14*, 695. [CrossRef]
5. Al Mamun, F.; Hosen, I.; Misti, J.M.; Kaggwa, M.M.; Mamun, M.A. Mental disorders of Bangladeshi students during the COVID-19 pandemic: A systematic review. *Psychol. Res. Behav. Manag.* **2021**, *14*, 645. [CrossRef]
6. Mertens, G.; Gerritsen, L.; Duijndam, S.; Salemink, E.; Engelhard, I.M. Fear of the coronavirus (COVID-19): Predictors in an online study conducted in March 2020. *J. Anxiety Disord.* **2020**, *74*, 102258. [CrossRef] [PubMed]
7. Benson, H.; Beary, J.F.; Carol, M.P. The relaxation response. *Psychiatry* **1974**, *37*, 37–46. [CrossRef]
8. Bernstein, D.A.; Borkovec, T.D. *Progressive Relaxation Training: A Manual for the Helping Professions*; Research Press: Champaign, IL, USA , 1973.
9. Basmajian, J.V. Clinical use of biofeedback in rehabilitation. *Psychosomatics* **1982**, *23*, 67–73. [CrossRef] [PubMed]
10. Chaves, J.F.; Barber, T.X. Cognitive strategies, experimenter modeling, and expectation in the attenuation of pain. *J. Abnorm. Psychol.* **1974**, *83*, 356. [CrossRef]
11. Edmonston, W.E., Jr. Neutral hypnosis as relaxation. *Am. J. Clin. Hypn.* **1977**, *20*, 69–75. [CrossRef]
12. Morse, D.R.; Martin, J.S.; Furst, M.L.; Dubin, L.L. A physiological and subjective evaluation of meditation, hypnosis, and relaxation. *Psychosom. Med.* **1977**, *39*, 304–324. [CrossRef]
13. Shapiro, D.A.; Shapiro, D. Meta-analysis of comparative therapy outcome studies: A replication and refinement. *Psychol. Bull.* **1982**, *92*, 581. [CrossRef]
14. Achterberg, J.; Healing, I.I. *Shamanism and Modern Medicine*; Shambala: Boston, MA, USA; London, UK, 1985.
15. Shafer, K.C.; Greenfield, F. *Asthma Free in 21 Days: The Breakthrough Mind-Body Healing Program*; Harper: San Francisco, CA, USA, 2000.
16. Heinschel, J.A. A descriptive study of the interactive guided imagery experience. *J. Holist. Nurs.* **2002**, *20*, 325–346. [CrossRef] [PubMed]
17. Donaldson, M.S.; Corrigan, J.M.; Kohn, L.T. *To Err Is Human: Building a Safer Health System*; National Academies Press: Washington, DC, USA, 2000.
18. Trakhtenberg, E.C. The effects of guided imagery on the immune system: A critical review. *Int. J. Neurosci.* **2008**, *118*, 839–855. [CrossRef] [PubMed]
19. De Paolis, G.; Naccarato, A.; Cibelli, F.; D'Alete, A.; Mastroianni, C.; Surdo, L.; Casale, G.; Magnani, C. The effectiveness of progressive muscle relaxation and interactive guided imagery as a pain-reducing intervention in advanced cancer patients: A multicentre randomised controlled non-pharmacological trial. *Complement. Ther. Clin. Pract.* **2019**, *34*, 280–287. [CrossRef] [PubMed]
20. Sabatinelli, D.; Lang, P.J.; Bradley, M.M.; Flaisch, T. The neural basis of narrative imagery: Emotion and action. *Prog. Brain Res.* **2006**, *156*, 93–103. [PubMed]
21. Fox, A.S.; Kalin, N.H. A translational neuroscience approach to understanding the development of social anxiety disorder and its pathophysiology. *Am. J. Psychiatry* **2014**, *171*, 1162–1173. [CrossRef]
22. Perich, T.; Manicavasagar, V.; Mitchell, P.B.; Ball, J.R. The association between meditation practice and treatment outcome in mindfulness-based cognitive therapy for bipolar disorder. *Behav. Res. Ther.* **2013**, *51*, 338–343. [CrossRef]
23. Shapiro, S.L. The integration of mindfulness and psychology. *J. Clin. Psychol.* **2009**, *65*, 555–560. [CrossRef] [PubMed]
24. Vøllestad, J.; Nielsen, M.B.; Nielsen, G.H. Mindfulness-and acceptance-based interventions for anxiety disorders: A systematic review and meta-analysis. *Br. J. Clin. Psychol.* **2012**, *51*, 239–260. [CrossRef]

25. Williams, J.M.G.; Crane, C.; Barnhofer, T.; Brennan, K.; Duggan, D.S.; Fennell, M.J.; Hackmann, A.; Krusche, A.; Muse, K.; Von Rohr, I.R.; et al. Mindfulness-based cognitive therapy for preventing relapse in recurrent depression: A randomized dismantling trial. *J. Consult. Clin. Psychol.* **2014**, *82*, 275. [CrossRef] [PubMed]
26. Hudetz, J.A.; Hudetz, A.G.; Klayman, J. Relationship between relaxation by guided imagery and performance of working memory. *Psychol. Rep.* **2000**, *86*, 15–20. [CrossRef]
27. Pelletier, A.M. Three uses of guided imagery in hypnosis. *Am. J. Clin. Hypn.* **1979**, *22*, 32–36. [CrossRef] [PubMed]
28. Simonton, O.C.; Matthews-Simonton, S.; Sparks, T.F. Psychological intervention in the treatment of cancer. *Psychosomatics* **1980**, *21*, 226–233. [CrossRef] [PubMed]
29. Herman, J.P.; Figueiredo, H.; Mueller, N.K.; Ulrich-Lai, Y.; Ostrander, M.M.; Choi, D.C.; Cullinan, W.E. Central mechanisms of stress integration: Hierarchical circuitry controlling hypothalamo–pituitary–adrenocortical responsiveness. *Front. Neuroendocrinol.* **2003**, *24*, 151–180. [CrossRef]
30. McEwen, B.S.; Gianaros, P.J. Stress-and allostasis-induced brain plasticity. *Annu. Rev. Med.* **2011**, *62*, 431–445. [CrossRef]
31. Klimesch, W. EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Res. Rev.* **1999**, *29*, 169–195. [CrossRef]
32. Tran, Y.; Thuraisingham, R.; Wijesuriya, N.; Nguyen, H.; Craig, A. Detecting neural changes during stress and fatigue effectively: A comparison of spectral analysis and sample entropy. In Proceedings of the 2007 3rd International IEEE/EMBS Conference on Neural Engineering, Kohala Coast, HI, USA, 2–5 May 2007; pp. 350–353.
33. Stern, E.R.; Gonzalez, R.; Welsh, R.C.; Taylor, S.F. Updating beliefs for a decision: Neural correlates of uncertainty and underconfidence. *J. Neurosci.* **2010**, *30*, 8032–8041. [CrossRef]
34. Lewis, R.S.; Weekes, N.Y.; Wang, T.H. The effect of a naturalistic stressor on frontal EEG asymmetry, stress, and health. *Biol. Psychol.* **2007**, *75*, 239–247. [CrossRef]
35. Alonso, J.; Romero, S.; Ballester, M.; Antonijoan, R.; Mañanas, M. Stress assessment based on EEG univariate features and functional connectivity measures. *Physiol. Meas.* **2015**, *36*, 1351. [CrossRef]
36. Hebert, R.; Lehmann, D.; Tan, G.; Travis, F.; Arenander, A. Enhanced EEG alpha time-domain phase synchrony during Transcendental Meditation: Implications for cortical integration theory. *Signal Process.* **2005**, *85*, 2213–2232. [CrossRef]
37. Travis, F. Autonomic and EEG patterns distinguish transcending from other experiences during Transcendental Meditation practice. *Int. J. Psychophysiol.* **2001**, *42*, 1–9. [CrossRef]
38. Cahn, B.R.; Delorme, A.; Polich, J. Event-related delta, theta, alpha and gamma correlates to auditory oddball processing during Vipassana meditation. *Soc. Cogn. Affect. Neurosci.* **2013**, *8*, 100–111. [CrossRef]
39. Braboszcz, C.; Cahn, B.R.; Levy, J.; Fernandez, M.; Delorme, A. Increased gamma brainwave amplitude compared to control in three different meditation traditions. *PLoS ONE* **2017**, *12*, e0170647. [CrossRef] [PubMed]
40. Phneah, S.W.; Nisar, H. EEG-based alpha neurofeedback training for mood enhancement. *Australas. Phys. Eng. Sci. Med.* **2017**, *40*, 325–336. [CrossRef] [PubMed]
41. Zoefel, B.; Huster, R.J.; Herrmann, C.S. Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. *Neuroimage* **2011**, *54*, 1427–1431. [CrossRef]
42. Hudetz, J.A.; Hudetz, A.G.; Reddy, D.M. Effect of relaxation on working memory and the Bispectral Index of the EEG. *Psychol. Rep.* **2004**, *95*, 53–70. [CrossRef]
43. Fu, H.; Garrett, B.; Tao, G.; Cordingley, E.; Ofoghi, Z.; Taverner, T.; Sun, C.; Cheung, T. Virtual Reality–Guided Meditation for Chronic Pain in Patients With Cancer: Exploratory Analysis of Electroencephalograph Activity. *JMIR Biomed. Eng.* **2021**, *6*, e26332. [CrossRef]
44. Kbah, S.N.S. A computational model of the brain cortex and its synchronization. *BioMed Res. Int.* **2020**, *2020*, 3874626. [CrossRef]
45. Perez-Valero, E.; Vaquero-Blasco, M.A.; Lopez-Gordo, M.A.; Morillas, C. Quantitative assessment of stress through EEG during a virtual reality stress-relax session. *Front. Comput. Neurosci.* **2021**, *15*, 684423. [CrossRef] [PubMed]
46. Wada, Y.; Takizawa, Y.; Zheng-Yan, J.; Yamaguchi, N. Gender differences in quantitative EEG at rest and during photic stimulation in normal young adults. *Clin. Electroencephalogr.* **1994**, *25*, 81–85. [CrossRef] [PubMed]
47. Cantillo-Negrete, J.; Carino-Escobar, R.I.; Carrillo-Mora, P.; Flores-Rodríguez, T.B.; Elias-Vinas, D.; Gutierrez-Martinez, J. Gender differences in quantitative electroencephalogram during a simple hand movement task in young adults. *Rev. Investig. Clin.* **2017**, *68*, 245–255.
48. Tusek, D.L.; Church, J.M.; Strong, S.A.; Grass, J.A.; Fazio, V.W. Guided imagery. *Dis. Colon Rectum* **1997**, *40*, 172–178. [CrossRef]
49. Hart, J. Guided imagery. *Altern. Complement. Ther.* **2008**, *14*, 295–299. [CrossRef]
50. Roffe, L.; Schmidt, K.; Ernst, E. A systematic review of guided imagery as an adjuvant cancer therapy. *Psycho-Oncology* **2005**, *14*, 607–617. [CrossRef] [PubMed]
51. Dyląg, K.A.; Wieczorek, W.; Bauer, W.; Walecki, P.; Bando, B.; Martinek, R.; Kawala-Sterniuk, A. Pilot Study on Analysis of Electroencephalography Signals from Children with FASD with the Implementation of Naive Bayesian Classifiers. *Sensors* **2021**, *22*, 103. [CrossRef]
52. Mikołajewska, E.; Mikołajewski, D. Non-invasive EEG-based brain-computer interfaces in patients with disorders of consciousness. *Mil. Med. Res.* **2014**, *1*, 14. [CrossRef] [PubMed]
53. Salankar, N.; Qaisar, S.M.; Pławiak, P.; Tadeusiewicz, R.; Hammad, M. EEG based alcoholism detection by oscillatory modes decomposition second order difference plots and machine learning. *Biocybern. Biomed. Eng.* **2022**, *42*, 173–186. [CrossRef]

54. John, E.R.; Prichep, L.; Fridman, J.; Easton, P. Neurometrics: Computer-assisted differential diagnosis of brain dysfunctions. *Science* **1988**, *239*, 162–169. [CrossRef]
55. Wojcik, G.M.; Masiak, J.; Kawiak, A.; Kwasniewicz, L.; Schneider, P.; Postepski, F.; Gajos-Balinska, A. Analysis of decision-making process using methods of quantitative electroencephalography and machine learning tools. *Front. Neuroinform.* **2019**, *13*, 73. [CrossRef]
56. Wojcik, G.M.; Masiak, J.; Kawiak, A.; Schneider, P.; Kwasniewicz, L.; Polak, N.; Gajos-Balinska, A. New protocol for quantitative analysis of brain cortex electroencephalographic activity in patients with psychiatric disorders. *Front. Neuroinform.* **2018**, *12*, 27. [CrossRef] [PubMed]
57. Tadeusiewicz, R. Neural networks as a tool for modeling of biological systems. *Bio-Algorithms-Med-Syst.* **2015**, *11*, 135–144. [CrossRef]
58. Ważny, M.; Wojcik, G.M. Shifting spatial attention—numerical model of Posner experiment. *Neurocomputing* **2014**, *135*, 139–144. [CrossRef]
59. Wojcik, G.M.; Kaminski, W.A.; Matejanka, P. Self-organised criticality in a model of the rat somatosensory cortex. In *Proceedings of the Parallel Computing Technologies: 9th International Conference, PaCT 2007, Pereslavl-Zalessky, Russia, 3–7 September 2007*; Springer: Berlin/Heidelberg, Germany, 2007; pp. 468–476.
60. Wojcik, G.M.; Garcia-Lazaro, J.A. Analysis of the neural hypercolumn in parallel pcsim simulations. *Procedia Comput. Sci.* **2010**, *1*, 845–854. [CrossRef]
61. Kawala-Sterniuk, A.; Podpora, M.; Pelc, M.; Blaszczyszyn, M.; Gorzelanczyk, E.J.; Martinek, R.; Ozana, S. Comparison of smoothing filters in analysis of EEG data for the medical diagnostics purposes. *Sensors* **2020**, *20*, 807. [CrossRef] [PubMed]
62. Wójcik, G.M.; Kawiak, A.; Kwasniewicz, L.; Schneider, P.; Masiak, J. Azure machine learning tools efficiency in the electroencephalographic signal P300 standard and target responses classification. *Bio-Algorithms-Med-Syst.* **2019**, *15*. [CrossRef]
63. Wojcik, G.M.; Masiak, J.; Kawiak, A.; Kwasniewicz, L.; Schneider, P.; Polak, N.; Gajos-Balinska, A. Mapping the human brain in frequency band analysis of brain cortex electroencephalographic activity for selected psychiatric disorders. *Front. Neuroinform.* **2018**, *12*, 73. [CrossRef]
64. Kawala-Sterniuk, A.; Browarska, N.; Al-Bakri, A.; Pelc, M.; Zygarlicki, J.; Sidikova, M.; Martinek, R.; Gorzelanczyk, E.J. Summary of over fifty years with brain-computer interfaces—A review. *Brain Sci.* **2021**, *11*, 43. [CrossRef]
65. Wierzgała, P.; Zapała, D.; Wojcik, G.M.; Masiak, J. Most popular signal processing methods in motor-imagery BCI: A review and meta-analysis. *Front. Neuroinform.* **2018**, *12*, 78. [CrossRef]
66. Mikołajewska, E.; Mikołajewski, D. Ethical considerations in the use of brain-computer interfaces. *Cent. Eur. J. Med.* **2013**, *8*, 720–724. [CrossRef]
67. Mikołajewska, E.; Mikołajewski, D. The prospects of brain-computer interface applications in children. *Open Med.* **2014**, *9*, 74–79. [CrossRef]
68. Zhang, J. Development of an Apache Spark-Based Framework for Processing and Analyzing Neuroscience Big Data: Application in Epilepsy Using EEG Signal Data. Ph.D. Thesis, Case Western Reserve University, Cleveland, OH, USA, 2020.

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

sensors

Article

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

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

[1] Institute of Psychology, SWPS University of Social Sciences and Humanities, 03-815 Warsaw, Poland; kzemla1@st.swps.edu.pl (K.Z.)
[2] Department of Neuroinformatics and Biomedical Engineering, Institute of Computer Science, Maria Curie-Sklodowska University, 20-033 Lublin, Poland; filip.postepski@mail.umcs.pl (F.P.)
* Correspondence: gmwojcik@live.umcs.edu.pl; Tel.: +48-81-537-2940

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

check for updates

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

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.

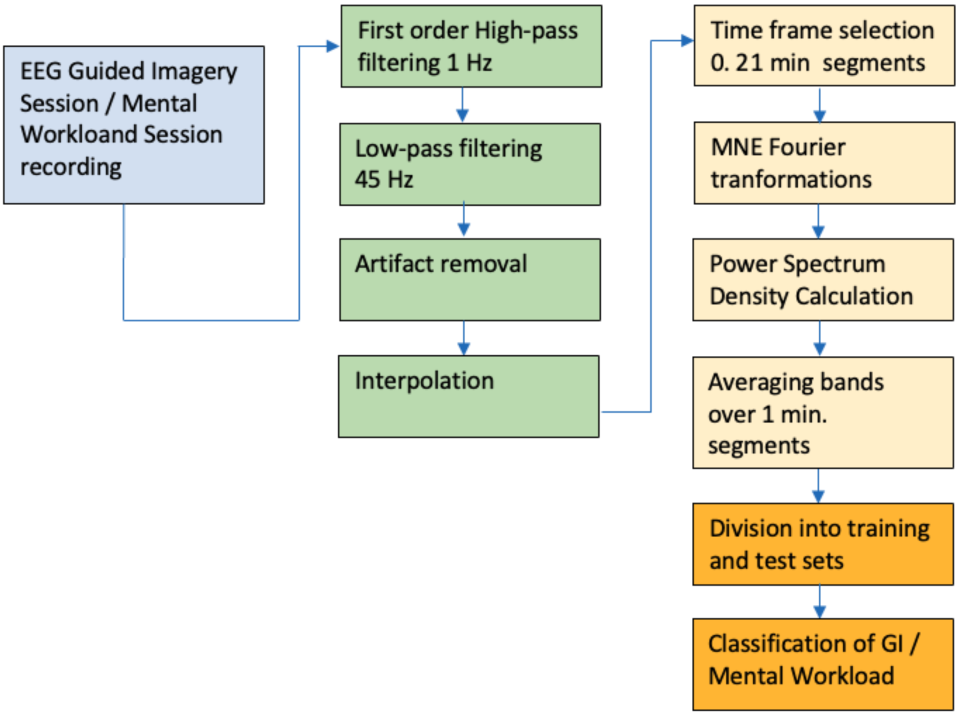

Figure 1. Research protocol used for data processing of both types of sessions: GI and mental task workloads.

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).

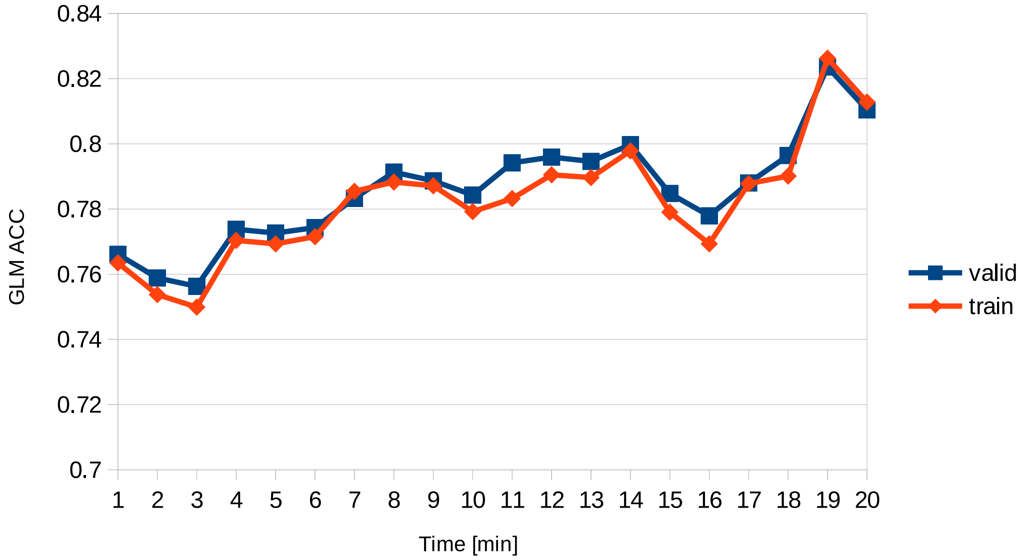

Figure 2. The 14th min choice justification.

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.

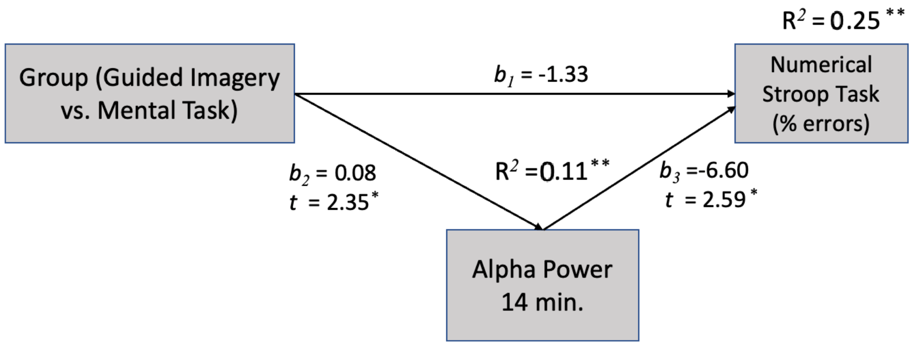

Figure 3. The effect of GI on reducing erroneous reactions in the Stroop test is mediated by the alpha power at 14 min. * $p < 0.05$, ** $p < 0.01$.

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.

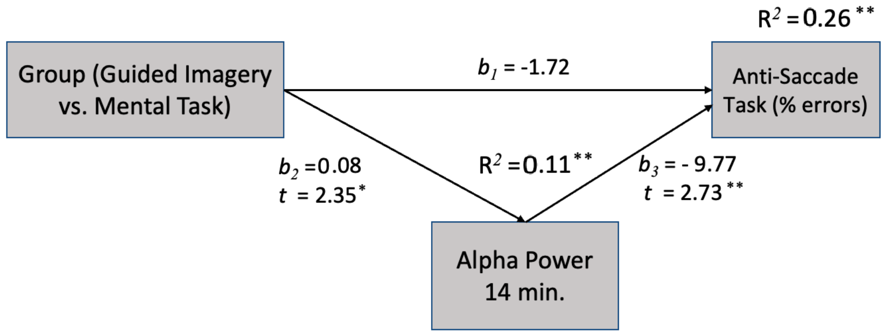

Figure 4. The effect of GI on reducing erroneous reactions in the anti-saccade test is mediated by the alpha power at 14 min. * $p < 0.05$, ** $p < 0.01$.

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.

References

1. Stevens, C.; Bavelier, D. The role of selective attention on academic foundations: A cognitive neuroscience perspective. *Dev. Cogn. Neurosci.* **2012**, *2*, S30–S48. [CrossRef]
2. Johnson, A.; Proctor, R.W. *Attention: Theory and Practice*; Sage: Thousand Oaks, CA, USA, 2004.
3. Trautwein, F.M.; Kanske, P.; Böckler, A.; Singer, T. Differential benefits of mental training types for attention, compassion, and theory of mind. *Cognition* **2020**, *194*, 104039. [CrossRef]
4. Peterson, R.L.; Boada, R.; McGrath, L.M.; Willcutt, E.G.; Olson, R.K.; Pennington, B.F. Cognitive prediction of reading, math, and attention: Shared and unique influences. *J. Learn. Disabil.* **2017**, *50*, 408–421. [CrossRef]
5. Arrington, C.N.; Kulesz, P.A.; Francis, D.J.; Fletcher, J.M.; Barnes, M.A. The contribution of attentional control and working memory to reading comprehension and decoding. *Sci. Stud. Read.* **2014**, *18*, 325–346. [CrossRef]
6. Titz, C.; Karbach, J. Working memory and executive functions: Effects of training on academic achievement. *Psychol. Res.* **2014**, *78*, 852–868. [CrossRef]
7. King, E.; Haar, J.M. Mindfulness and job performance: A study of Australian leaders. *Asia Pac. J. Hum. Resour.* **2017**, *55*, 298–319. [CrossRef]
8. Gao, C.; Zhao, X.; Li, T. Effects of indoor VOCs from paint on human brain activities during working memory tasks: An electroencephalogram study. *Indoor Air* **2022**, *32*, e13062. [CrossRef] [PubMed]
9. Tang, Y.Y.; Lu, Q.; Feng, H.; Tang, R.; Posner, M.I. Short-term meditation increases blood flow in anterior cingulate cortex and insula. *Front. Psychol.* **2015**, *6*, 212. [CrossRef] [PubMed]
10. Zeidan, F.; Johnson, S.K.; Diamond, B.J.; David, Z.; Goolkasian, P. Mindfulness meditation improves cognition: Evidence of brief mental training. *Conscious. Cogn.* **2010**, *19*, 597–605. [CrossRef] [PubMed]
11. Ruedy, N.E.; Schweitzer, M.E. In the moment: The effect of mindfulness on ethical decision making. *J. Bus. Ethics* **2010**, *95*, 73–87. [CrossRef]
12. Chiesa, A.; Serretti, A. A systematic review of neurobiological and clinical features of mindfulness meditations. *Psychol. Med.* **2010**, *40*, 1239–1252. [CrossRef]
13. Malinowski, P. Neural mechanisms of attentional control in mindfulness meditation. *Front. Neurosci.* **2013**, *7*, 8. [CrossRef]

14. Gallant, S.N. Mindfulness meditation practice and executive functioning: Breaking down the benefit. *Conscious. Cogn.* **2016**, *40*, 116–130. [CrossRef] [PubMed]
15. Chiesa, A.; Calati, R.; Serretti, A. Does mindfulness training improve cognitive abilities? A systematic review of neuropsychological findings. *Clin. Psychol. Rev.* **2011**, *31*, 449–464. [CrossRef] [PubMed]
16. Cahn, B.R.; Polich, J. Meditation states and traits: EEG, ERP, and neuroimaging studies. *Psychol. Bull.* **2006**, *132*, 180. [CrossRef]
17. Raffone, A.; Srinivasan, N. Mindfulness and cognitive functions: Toward a unifying neurocognitive framework. *Mindfulness* **2017**, *8*, 1–9. [CrossRef]
18. Achterberg, J.; Healing, I.I. *Shamanism and Modern Medicine*; Shambhala: Boulder, CO, USA, 1985.
19. Kwekkeboom, K.L. Outcome expectancy and success with cognitive-behavioral interventions: The case of guided imagery. *Oncol. Nurs. Forum* **2001**, *28*, 1125–1132.
20. Cooley, S.J.; Williams, S.E.; Burns, V.E.; Cumming, J. Methodological variations in guided imagery interventions using movement imagery scripts in sport: A systematic review. *J. Imag. Res. Sport Phys. Act.* **2013**, *8*, 13–34. [CrossRef]
21. Pelletier, K.R. *Mind As Healer, Mind As Slayer: A Holistic Approach to Preventing Stress Disorders*; Dell: New York, NY, USA, 1977.
22. Simonton, O.C.; Matthews-Simonton, S.; Sparks, T.F. Psychological intervention in the treatment of cancer. *Psychosomatics* **1980**, *21*, 226–233. [CrossRef]
23. Vines, S.W. Relaxation with guided imagery: Effects on employees' psychological distress and health seeking behaviors. *AAOHN J.* **1994**, *42*, 206–213. [CrossRef]
24. Hart, J. Guided imagery. *Altern. Complement. Ther.* **2008**, *14*, 295–299. [CrossRef]
25. Achterberg, J. *Imagery in Healing: Shamanism and Modern Science*; New Science Library: Boston, MA, USA, 1985.
26. Wachelka, D.; Katz, R.C. Reducing test anxiety and improving academic self-esteem in high school and college students with learning disabilities. *J. Behav. Ther. Exp. Psychiatry* **1999**, *30*, 191–198. [CrossRef] [PubMed]
27. Gruzelier, J.; Smith, F.; Nagy, A.; Henderson, D. Cellular and humoral immunity, mood and exam stress: The influences of self-hypnosis and personality predictors. *Int. J. Psychophysiol.* **2001**, *42*, 55–71. [CrossRef] [PubMed]
28. Ayres, J.; Hopf, T.S. Visualization: A means of reducing speech anxiety. *Commun. Educ.* **1985**, *34*, 318–323. [CrossRef]
29. Speck, B.J. The effect of guided imagery upon first semester nursing students performing their first injections. *J. Nurs. Educ.* **1990**, *29*, 346–350. [CrossRef]
30. Stephens, R.L. Imagery: A treatment for nursing student anxiety. *J. Nurs. Educ.* **1992**, *31*, 314–320. [CrossRef] [PubMed]
31. Rees, B.L. Effect of relaxation with guided imagery on anxiety, depression, and self-esteem in primiparas. *J. Holist. Nurs.* **1995**, *13*, 255–267. [CrossRef]
32. Thomas, K.M.; Sethares, K.A. Is guided imagery effective in reducing pain and anxiety in the postoperative total joint arthroplasty patient? *Orthop. Nurs.* **2010**, *29*, 393–399. [CrossRef]
33. Kapoor, V.G.; Bray, M.A.; Kehle, T.J. School-based intervention: Relaxation and guided imagery for students with asthma and anxiety disorder. *Can. J. Sch. Psychol.* **2010**, *25*, 311–327. [CrossRef]
34. Serra, D.; Parris, C.R.; Carper, E.; Homel, P.; Fleishman, S.B.; Harrison, L.B.; Chadha, M. Outcomes of guided imagery in patients receiving radiation therapy for breast cancer. *Clin. J. Oncol. Nurs.* **2012**, *16*. [CrossRef]
35. Nguyen, J.; Brymer, E. Nature-based guided imagery as an intervention for state anxiety. *Front. Psychol.* **2018**, *9*, 1858. [CrossRef]
36. Singh, B.; Pandey, S. Spiritual Healing and Rajyoga Meditation in Schizo-Affective Disorder, Depressive Type—A Case Report. *Int. J. Sci. Res.* **2015**, *4*, SUB151884.
37. Krishnakumar, D.; Hamblin, M.R.; Lakshmanan, S. Meditation and yoga can modulate brain mechanisms that affect behavior and anxiety—A modern scientific perspective. *Anc. Sci.* **2015**, *2*, 13. [CrossRef]
38. Stapleton, P.; Dispenza, J.; McGill, S.; Sabot, D.; Peach, M.; Raynor, D. Large effects of brief meditation intervention on EEG spectra in meditation novices. *IBRO Rep.* **2020**, *9*, 290–301. [CrossRef] [PubMed]
39. Bohlmeijer, E.; Prenger, R.; Taal, E.; Cuijpers, P. The effects of mindfulness-based stress reduction therapy on mental health of adults with a chronic medical disease: A meta-analysis. *J. Psychosom. Res.* **2010**, *68*, 539–544. [CrossRef]
40. Tang, Y.Y.; Hölzel, B.K.; Posner, M.I. The neuroscience of mindfulness meditation. *Nat. Rev. Neurosci.* **2015**, *16*, 213–225. [CrossRef]
41. Fox, A.S.; Kalin, N.H. A translational neuroscience approach to understanding the development of social anxiety disorder and its pathophysiology. *Am. J. Psychiatry* **2014**, *171*, 1162–1173. [CrossRef] [PubMed]
42. Perich, T.; Manicavasagar, V.; Mitchell, P.B.; Ball, J.R. The association between meditation practice and treatment outcome in mindfulness-based cognitive therapy for bipolar disorder. *Behav. Res. Ther.* **2013**, *51*, 338–343. [CrossRef]
43. Shapiro, S.L. The integration of mindfulness and psychology. *J. Clin. Psychol.* **2009**, *65*, 555–560. [CrossRef]
44. Vøllestad, J.; Nielsen, M.B.; Nielsen, G.H. Mindfulness-and acceptance-based interventions for anxiety disorders: A systematic review and meta-analysis. *Br. J. Clin. Psychol.* **2012**, *51*, 239–260. [CrossRef] [PubMed]
45. Williams, J.M.G.; Crane, C.; Barnhofer, T.; Brennan, K.; Duggan, D.S.; Fennell, M.J.; Hackmann, A.; Krusche, A.; Muse, K.; Von Rohr, I.R.; et al. Mindfulness-based cognitive therapy for preventing relapse in recurrent depression: A randomized dismantling trial. *J. Consult. Clin. Psychol.* **2014**, *82*, 275. [CrossRef]
46. Hebert, R.; Lehmann, D.; Tan, G.; Travis, F.; Arenander, A. Enhanced EEG alpha time-domain phase synchrony during Transcendental Meditation: Implications for cortical integration theory. *Signal Process.* **2005**, *85*, 2213–2232. [CrossRef]
47. Atchley, R.; Klee, D.; Memmott, T.; Goodrich, E.; Wahbeh, H.; Oken, B. Event-related potential correlates of mindfulness meditation competence. *Neuroscience* **2016**, *320*, 83–92. [CrossRef] [PubMed]

48. Phneah, S.W.; Nisar, H. EEG-based alpha neurofeedback training for mood enhancement. *Australas. Phys. Eng. Sci. Med.* **2017**, *40*, 325–336. [CrossRef]
49. Klimesch, W. EEG alpha and theta oscillations reflect cognitive and memory performance: A review and analysis. *Brain Res. Rev.* **1999**, *29*, 169–195. [CrossRef]
50. Sulaiman, N.; Taib, M.N.; Lias, S.; Murat, Z.H.; Aris, S.A.M.; Mustafa, M.; Rashid, N.A. Development of EEG-based stress index. In Proceedings of the 2012 International Conference on Biomedical Engineering (ICoBE), Penang, Malaysia, 27–28 February 2012; IEEE: Piscataway, NJ, USA, 2012; pp. 461–466.
51. Scholz, U.; La Marca, R.; Nater, U.M.; Aberle, I.; Ehlert, U.; Hornung, R.; Martin, M.; Kliegel, M. Go no-go performance under psychosocial stress: Beneficial effects of implementation intentions. *Neurobiol. Learn. Mem.* **2009**, *91*, 89–92. [CrossRef]
52. Zoefel, B.; Huster, R.J.; Herrmann, C.S. Neurofeedback training of the upper alpha frequency band in EEG improves cognitive performance. *Neuroimage* **2011**, *54*, 1427–1431. [CrossRef] [PubMed]
53. Friedman, N.P.; Robbins, T.W. The role of prefrontal cortex in cognitive control and executive function. *Neuropsychopharmacology* **2022**, *47*, 72–89. [CrossRef] [PubMed]
54. Miyake, A.; Friedman, N.P.; Emerson, M.J.; Witzki, A.H.; Howerter, A.; Wager, T.D. The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cogn. Psychol.* **2000**, *41*, 49–100. [CrossRef] [PubMed]
55. Diamond, A. Executive functions. *Annu. Rev. Psychol.* **2013**, *64*, 135–168. [CrossRef] [PubMed]
56. MacLeod, C.M. Half a century of research on the Stroop effect: An integrative review. *Psychol. Bull.* **1991**, *109*, 163. [CrossRef]
57. Hellmuth, J.; Mirsky, J.; Heuer, H.; Matlin, A.; Jafari, A.; Garbutt, S.; Widmeyer, M.; Berhel, A.; Sinha, L.; Miller, B.; et al. Multicenter validation of a bedside antisaccade task as a measure of executive function. *Neurology* **2012**, *78*, 1824–1831. [CrossRef] [PubMed]
58. Meule, A. Reporting and interpreting task performance in go/no-go affective shifting tasks. *Front. Psychol.* **2017**, *8*, 701. [CrossRef] [PubMed]
59. Chan, D.; Woollacott, M. Effects of level of meditation experience on attentional focus: Is the efficiency of executive or orientation networks improved? *J. Altern. Complement. Med.* **2007**, *13*, 651–658. [CrossRef] [PubMed]
60. Moore, A.; Malinowski, P. Meditation, mindfulness and cognitive flexibility. *Conscious. Cogn.* **2009**, *18*, 176–186. [CrossRef]
61. Bing-Canar, H.; Pizzuto, J.; Compton, R.J. Mindfulness-of-breathing exercise modulates EEG alpha activity during cognitive performance. *Psychophysiology* **2016**, *53*, 1366–1376. [CrossRef]
62. Fan, Y.; Tang, Y.Y.; Tang, R.; Posner, M.I. Short term integrative meditation improves resting alpha activity and stroop performance. *Appl. Psychophysiol. Biofeedback* **2014**, *39*, 213–217. [CrossRef]
63. Kumari, V.; Antonova, E.; Wright, B.; Hamid, A.; Hernandez, E.M.; Schmechtig, A.; Ettinger, U. The mindful eye: Smooth pursuit and saccadic eye movements in meditators and non-meditators. *Conscious. Cogn.* **2017**, *48*, 66–75. [CrossRef]
64. Keith, J.R.; Blackwood, M.E.; Mathew, R.T.; Lecci, L.B. Self-reported mindful attention and awareness, go/no-go response-time variability, and attention-deficit hyperactivity disorder. *Mindfulness* **2017**, *8*, 765–774. [CrossRef]
65. Brown, K.W.; Ryan, R.M. The benefits of being present: Mindfulness and its role in psychological well-being. *J. Personal. Soc. Psychol.* **2003**, *84*, 822. [CrossRef]
66. Feldman, G.; Hayes, A.; Kumar, S.; Greeson, J.; Laurenceau, J.P. Mindfulness and emotion regulation: The development and initial validation of the Cognitive and Affective Mindfulness Scale-Revised (CAMS-R). *J. Psychopathol. Behav. Assess.* **2007**, *29*, 177–190. [CrossRef]
67. Mrazek, M.D.; Mooneyham, B.W.; Schooler, J.W. Insights from quiet minds: The converging fields of mindfulness and mind-wandering. In *Meditation—Neuroscientific Approaches and Philosophical Implications*; Springer: Berlin/Heidelberg, Germany, 2014; pp. 227–241.
68. Schmertz, S.K. The relation between self-report mindfulness and performance on tasks of attention. *J. Psychopathol. Behav. Assess.* **2006**, *31*, 60–66. [CrossRef]
69. Holas, P.; Jankowski, T. A cognitive perspective on mindfulness. *Int. J. Psychol.* **2013**, *48*, 232–243. [CrossRef] [PubMed]
70. Baranski, M.F. *The Effects of Mindfulness Meditation on Executive Functions, Moderated by Trait Anxiety*; Kent State University: Kent, OH, USA, 2020.
71. Hudetz, J.A.; Hudetz, A.G.; Klayman, J. Relationship between relaxation by guided imagery and performance of working memory. *Psychol. Rep.* **2000**, *86*, 15–20. [CrossRef]
72. Hudetz, J.A.; Hudetz, A.G.; Reddy, D.M. Effect of relaxation on working memory and the Bispectral Index of the EEG. *Psychol. Rep.* **2004**, *95*, 53–70. [CrossRef]
73. Shapiro, S.L.; Carlson, L.E.; Astin, J.A.; Freedman, B. Mechanisms of mindfulness. *J. Clin. Psychol.* **2006**, *62*, 373–386. [CrossRef]
74. Angelidis, A.; Solis, E.; Lautenbach, F.; van der Does, W.; Putman, P. I'm going to fail! Acute cognitive performance anxiety increases threat-interference and impairs WM performance. *PLoS ONE* **2019**, *14*, e0210824. [CrossRef] [PubMed]
75. Eysenck, M.W.; Derakshan, N.; Santos, R.; Calvo, M.G. Anxiety and cognitive performance: Attentional control theory. *Emotion* **2007**, *7*, 336. [CrossRef]
76. Shi, R.; Sharpe, L.; Abbott, M. A meta-analysis of the relationship between anxiety and attentional control. *Clin. Psychol. Rev.* **2019**, *72*, 101754. [CrossRef]
77. Spielberger, C.D. *State-Trait Anxiety Inventory for Adults*; APA PsycTests: Washington, DC, USA, 1983.

78. Huang, F.Y.; Hsu, A.L.; Hsu, L.M.; Tsai, J.S.; Huang, C.M.; Chao, Y.P.; Hwang, T.J.; Wu, C.W. Mindfulness improves emotion regulation and executive control on bereaved individuals: An fMRI study. *Front. Hum. Neurosci.* **2019**, *12*, 541. [CrossRef]
79. Tousignant, O.H.; Taylor, N.D.; Suvak, M.K.; Fireman, G.D. Effects of rumination and worry on sleep. *Behav. Ther.* **2019**, *50*, 558–570. [CrossRef]
80. Kawiak, A.; Wójcik, G.M.; Kwasniewicz, L.; Schneider, P.; Wierzbicki, A. Look Who's Talking: Modeling Decision Making Based on Source Credibility. In Proceedings of the International Conference on Computational Science, Amsterdam, The Netherlands, 3–5 June 2020; Springer: Berlin/Heidelberg, Germany, 2020; pp. 327–341.
81. Kwaśniewicz, Ł.; Wójcik, G.M.; Kawiak, A.; Schneider, P.; Wierzbicki, A. How You Say or What You Say? Neural Activity in Message Credibility Evaluation. In Proceedings of the International Conference on Computational Science, Amsterdam, The Netherlands, 3–5 June 2020; Springer: Berlin/Heidelberg, Germany, 2020; pp. 312–326.
82. Schneider, P.; Wójcik, G.M.; Kawiak, A.; Kwasniewicz, L.; Wierzbicki, A. Modeling and Comparing Brain Processes in Message and Earned Source Credibility Evaluation. *Front. Hum. Neurosci.* **2022**, *16*, 808382. [CrossRef]
83. EGI. *Net Station Waveforms Tools Technical Manual*; Electrical Geodesics, Inc.: Eugene, OR, USA, 2006.
84. Wojcik, G.M.; Shriki, O.; Kwasniewicz, L.; Kawiak, A.; Ben-Horin, Y.; Furman, S.; Wróbel, K.; Bartosik, B.; Panas, E. Investigating brain cortical activity in patients with post-COVID-19 brain fog. *Front. Neurosci.* **2023**, *17*, 1019778. [CrossRef] [PubMed]
85. Wada, Y.; Takizawa, Y.; Zheng-Yan, J.; Yamaguchi, N. Gender differences in quantitative EEG at rest and during photic stimulation in normal young adults. *Clin. Electroencephalogr.* **1994**, *25*, 81–85. [CrossRef] [PubMed]
86. Cantillo-Negrete, J.; Carino-Escobar, R.I.; Carrillo-Mora, P.; Flores-Rodríguez, T.B.; Elias-Vinas, D.; Gutierrez-Martinez, J. Gender differences in quantitative electroencephalogram during a simple hand movement task in young adults. *Rev. Investig. Clin.* **2017**, *68*, 245–255.
87. McCullagh, P. *Generalized Linear Models*; Routledge: Hoboken, NJ, USA, 2019.
88. Dyląg, K.A.; Wieczorek, W.; Bauer, W.; Walecki, P.; Bando, B.; Martinek, R.; Kawala-Sterniuk, A. Pilot Study on Analysis of Electroencephalography Signals from Children with FASD with the Implementation of Naive Bayesian Classifiers. *Sensors* **2021**, *22*, 103. [CrossRef] [PubMed]
89. Mikołajewska, E.; Mikołajewski, D. Non-invasive EEG-based brain–computer interfaces in patients with disorders of consciousness. *Mil. Med. Res.* **2014**, *1*, 1–6. [CrossRef] [PubMed]
90. Salankar, N.; Qaisar, S.M.; Pławiak, P.; Tadeusiewicz, R.; Hammad, M. EEG based alcoholism detection by oscillatory modes decomposition second order difference plots and machine learning. *Biocybern. Biomed. Eng.* **2022**, *42*, 173–186. [CrossRef]
91. Wojcik, G.M.; Masiak, J.; Kawiak, A.; Schneider, P.; Kwasniewicz, L.; Polak, N.; Gajos-Balinska, A. New protocol for quantitative analysis of brain cortex electroencephalographic activity in patients with psychiatric disorders. *Front. Neuroinform.* **2018**, *12*, 27. [CrossRef]
92. Tadeusiewicz, R. Neural networks as a tool for modeling of biological systems. *Bio-Algorithms Med-Syst.* **2015**, *11*, 135–144. [CrossRef]
93. Ważny, M.; Wojcik, G.M. Shifting spatial attention—Numerical model of Posner experiment. *Neurocomputing* **2014**, *135*, 139–144. [CrossRef]
94. Wojcik, G.M.; Garcia-Lazaro, J.A. Analysis of the neural hypercolumn in parallel pcsim simulations. *Procedia Comput. Sci.* **2010**, *1*, 845–854. [CrossRef]
95. Wojcik, G.M.; Masiak, J.; Kawiak, A.; Kwasniewicz, L.; Schneider, P.; Polak, N.; Gajos-Balinska, A. Mapping the human brain in frequency band analysis of brain cortex electroencephalographic activity for selected psychiatric disorders. *Front. Neuroinform.* **2018**, *12*, 73. [CrossRef]
96. Wojcik, G.M.; Masiak, J.; Kawiak, A.T.; Kwasniewicz, L.K.; Schneider, P.; Postepski, F.; Gajos-Balinska, A. Analysis of decision-making process using methods of quantitative electroencephalography and machine learning tools. *Front. Neuroinform.* **2019**, *13*, 73. [CrossRef]
97. de Melo, M.B.; Daldegan-Bueno, D.; Menezes Oliveira, M.G.; de Souza, A.L. Beyond ANOVA and MANOVA for repeated measures: Advantages of generalized estimated equations and generalized linear mixed models and its use in neuroscience research. *Eur. J. Neurosci.* **2022**, *56*, 6089–6098. [CrossRef]
98. 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. [CrossRef]
99. Gruzelier, J. A review of the impact of hypnosis, relaxation, guided imagery and individual differences on aspects of immunity and health. *Stress* **2002**, *5*, 147–163. [CrossRef] [PubMed]
100. Cardaciotto, L.; Herbert, J.D.; Forman, E.M.; Moitra, E.; Farrow, V. The assessment of present-moment awareness and acceptance: The Philadelphia Mindfulness Scale. *Assessment* **2008**, *15*, 204–223. [CrossRef] [PubMed]
101. Rathee, S.; Bhatia, D.; Punia, V.; Singh, R. Peak alpha frequency in relation to cognitive performance. *J. Neurosci. Rural. Pract.* **2020**, *11*, 416–419. [CrossRef]
102. Koczkodaj, W.W. Statistically accurate evidence of improved error rate by pairwise comparisons. *Percept. Mot. Ski.* **1996**, *82*, 43–48. [CrossRef]
103. Sun, B.; Liu, Z.; Wu, Z.; Mu, C.; Li, T. Graph Convolution Neural Network based End-to-end Channel Selection and Classification for Motor Imagery Brain-computer Interfaces. *IEEE Trans. Ind. Inform.* **2022** , 1–10.. [CrossRef]

104. Li, T.; Duan, M.; Li, K.; Yu, G.; Ruan, Z. Bedside monitoring of patients with shock using a portable spatially-resolved near-infrared spectroscopy. *Biomed. Opt. Express* **2015**, *6*, 3431–3436. [CrossRef] [PubMed]
105. Li, T.; Lin, Y.; Shang, Y.; He, L.; Huang, C.; Szabunio, M.; Yu, G. Simultaneous measurement of deep tissue blood flow and oxygenation using noncontact diffuse correlation spectroscopy flow-oximeter. *Sci. Rep.* **2013**, *3*, 1358. [CrossRef]
106. Sun, B.; Wu, Z.; Hu, Y.; Li, T. Golden subject is everyone: A subject transfer neural network for motor imagery-based brain computer interfaces. *Neural Netw.* **2022**, *151*, 111–120. [CrossRef] [PubMed]

References

Achterberg, J. (1985). Imagery in healing: Shamanism and modern science. *Boston: New Science Library*.

Achterberg, J., & Lawlis, G. (1981). Imagery and terminal care: the therapist as shaman. In *Behavior therapy in terminal care.* Ballinger Cambridge, MA.

Arrington, C. N., Kulesz, P. A., Francis, D. J., Fletcher, J. M., & Barnes, M. A. (2014). The contribution of attentional control and working memory to reading comprehension and decoding. *Scientific Studies of Reading*, *18*(5), 325–346.

Barber, T., Spanos, N., & Chavez, J. (1974). Hypnotism. *Imagination and Human Potentialities. Nueva York: Pergamon*.

Basmajian, J. V. (1982). Clinical use of biofeedback in rehabilitation. *Psychosomatics*, *23*(1), 67–73.

Benson, H., Beary, J. F., & Carol, M. P. (1974). The relaxation response. *Psychiatry*, *37*(1), 37–46.

Bernstein, D. A., & Borkovec, T. D. (1973). *Progressive relaxation training: A manual for the helping professions.* ERIC.

Boucsein, W., & Boucsein, W. (2012). Principles of electrodermal phenomena. *Electrodermal Activity*, 1–86.

Brown, K. W., & Ryan, R. M. (2003). The benefits of being present: mindfulness and its role in psychological well-being. *Journal of personality and Social Psychology*, *84*(4), 822.

Cahn, B. R., & Polich, J. (2006). Meditation states and traits: Eeg, erp, and neuroimaging studies. *Psychological Bulletin*, *132*(2), 180.

Cantillo-Negrete, J., Carino-Escobar, R. I., Carrillo-Mora, P., Flores-Rodríguez, T. B., Elias-Vinas, D., & Gutierrez-Martinez, J. (2017). Gender differences in quantitative electroencephalogram during a simple hand movement task in young adults. *Revista de Investigación Clinica*, *68*(5), 245–255.

Carrington, P., Collings Jr, G. H., Benson, H., Robinson, H., Wood, L. W., Lehrer, P. M., ... Cole, J. W. (1980). The use of meditation–relaxation techniques for the management of stress in a working population. *Journal of Occupational Medicine.: Official Publication of the Industrial Medical Association*, *22*(4), 221–231.

Chambers, R., Lo, B. C. Y., & Allen, N. B. (2008). The impact of intensive mindfulness training on attentional control, cognitive style, and affect. *Cognitive Therapy and Research*, *32*, 303–322.

Chan, D., & Woollacott, M. (2007). Effects of level of meditation experience on attentional focus: is the efficiency of executive or orientation networks improved? *The Journal of Alternative and Complementary Medicine*, *13*(6), 651–658.

Chiesa, A., Calati, R., & Serretti, A. (2011). Does mindfulness training improve cognitive abilities? a systematic review of neuropsychological findings. *Clinical Psychology Review*, *31*(3), 449–464.

Chiesa, A., & Serretti, A. (2010). A systematic review of neurobiological and clinical features of mindfulness meditations. *Psychological Medicine*, *40*(8), 1239–1252.

Cooley, S. J., Williams, S. E., Burns, V. E., & Cumming, J. (2013). Methodological variations in guided imagery interventions using movement imagery scripts in sport: A systematic review. *Journal of Imagery Research in Sport and Physical Activity*, *8*(1), 13–34.

Course-Choi, J., Saville, H., & Derakshan, N. (2017). The effects of adaptive working memory training and mindfulness meditation training on processing efficiency and worry in high worriers. *Behaviour Research and*

Therapy, *89*, 1–13.

De Paolis, G., Naccarato, A., Cibelli, F., D'Alete, A., Mastroianni, C., Surdo, L., ... Magnani, C. (2019). The effectiveness of progressive muscle relaxation and interactive guided imagery as a pain-reducing intervention in advanced cancer patients: A multicentre randomised controlled non-pharmacological trial. *Complementary Therapies in Clinical Practice*, *34*, 280–287.

Diamond, A. (2013). Executive functions. *Annual Review of Psychology*, *64*, 135–168.

Edmonston Jr, W. E. (1977). Neutral hypnosis as relaxation. *American Journal of Clinical Hypnosis*, *20*(1), 69–75.

Fawzy, F., Fawzy, N., Hyun, C., Elashoff, R., Guthrie, D., Fahey, J., & Morton, D. (1993). Effects of an early structured psychiatric intervention, coping and affective state on recurrence and sumval 6 years later. *Archives of General Psvchiatry*, *50*(68), 1–688.

Feldman, G., Hayes, A., Kumar, S., Greeson, J., & Laurenceau, J.-P. (2007). Mindfulness and emotion regulation: The development and initial validation of the cognitive and affective mindfulness scale-revised (cams-r). *Journal of Psychopathology and Behavioral Assessment*, *29*, 177–190.

Foote, W. W. (1996). *Guided-imagery therapy.* Basic Books.

Friedman, H. S. (2015). *Encyclopedia of mental health.* Academic Press.

Friedman, N. P., & Robbins, T. W. (2022). The role of prefrontal cortex in cognitive control and executive function. *Neuropsychopharmacology*, *47*(1), 72–89.

Gallant, S. N. (2016). Mindfulness meditation practice and executive functioning: Breaking down the benefit. *Consciousness and Cognition*, *40*, 116–130.

Gao, C., Zhao, X., & Li, T. (2022). Effects of indoor vocs from paint on human brain activities during working memory tasks: An electroencephalogram study. *Indoor Air*, *32*(7), e13062.

Gruzelier, J., Smith, F., Nagy, A., & Henderson, D. (2001). Cellular and humoral immunity, mood and exam stress: the influences of self-hypnosis and personality predictors. *International Journal of Psychophysiology*, *42*(1), 55–71.

Hasenkamp, W., & Barsalou, L. W. (2012). Effects of meditation experience on functional connectivity of distributed brain networks. *Frontiers in Human Neuroscience*, *6*, 38.

Hebert, R., Lehmann, D., Tan, G., Travis, F., & Arenander, A. (2005). Enhanced eeg alpha time-domain phase synchrony during transcendental meditation: Implications for cortical integration theory. *Signal Processing*, *85*(11), 2213–2232.

Heinschel, J. A. (2002). A descriptive study of the interactive guided imagery experience. *Journal of Holistic Nursing*, *20*(4), 325–346.

Hellmuth, J., Mirsky, J., Heuer, H., Matlin, A., Jafari, A., Garbutt, S., ... others (2012). Multicenter validation of a bedside antisaccade task as a measure of executive function. *Neurology*, *78*(23), 1824–1831.

Herman, J. P., Figueiredo, H., Mueller, N. K., Ulrich-Lai, Y., Ostrander, M. M., Choi, D. C., & Cullinan, W. E. (2003). Central mechanisms of stress integration: hierarchical circuitry controlling hypothalamo–pituitary–adrenocortical responsiveness. *Frontiers in Neuroendocrinology*, *24*(3), 151–180.

Holas, P., & Jankowski, T. (2013). A cognitive perspective on mindfulness. *International Journal of Psychology*, *48*(3), 232–243.

Huang, F.-Y., Hsu, A.-L., Hsu, L.-M., Tsai, J.-S., Huang, C.-M., Chao, Y.-P.,

... Wu, C. W. (2019). Mindfulness improves emotion regulation and executive control on bereaved individuals: an fmri study. *Frontiers in Human Neuroscience*, *12*, 541.

Hudetz, J. A., Hudetz, A. G., & Klayman, J. (2000). Relationship between relaxation by guided imagery and performance of working memory. *Psychological Reports*, *86*(1), 15–20.

Jha, A. P., Krompinger, J., & Baime, M. J. (2007). Mindfulness training modifies subsystems of attention. *Cognitive, Affective, & Behavioral Neuroscience*, *7*(2), 109–119.

Johnson, A., & Proctor, R. W. (2004). *Attention: Theory and practice*. Sage.

Kabat-Zinn, J. (1990). Mindfulness-based stress reduction. *Using the Wisdom of Your Body and Mind to Face Stress, Pain, and Illness*, *467*.

Keith, J. R., Blackwood, M. E., Mathew, R. T., & Lecci, L. B. (2017). Self-reported mindful attention and awareness, go/no-go response-time variability, and attention-deficit hyperactivity disorder. *Mindfulness*, *8*, 765–774.

King, E., & Haar, J. M. (2017). Mindfulness and job performance: A study of australian leaders. *Asia Pacific Journal of Human Resources*, *55*(3), 298–319.

Koczkodaj, W., Mansournia, M., Pedrycz, e. W., Wolny-Dominiak, A., Zabrodskii, P., Strzałka, D., ... Mazurek, J. (2020). 1,000,000 cases of covid-19 outside of china: The date predicted by a simple heuristic. *Global Epidemiology*, *2*, 100023.

Koczkodaj, W. W. (1996). Statistically accurate evidence of improved error rate by pairwise comparisons. *Perceptual and Motor Skills*, *82*(1), 43–48.

Kwekkeboom, K. L. (2001). Outcome expectancy and success with cognitive-behavioral interventions: the case of guided imagery. In *Oncology nursing* *forum* (Vol. 28).

Lutz, A., Slagter, H. A., Dunne, J. D., & Davidson, R. J. (2008). Attention regulation and monitoring in meditation. *Trends in Cognitive Sciences*, *12*(4), 163–169.

MacLeod, C. M. (1991). Half a century of research on the stroop effect: an integrative review. *Psychological Bulletin*, *109*(2), 163.

Malinowski, P. (2013). Neural mechanisms of attentional control in mindfulness meditation. *Frontiers in Neuroscience*, *7*, 8.

Mamun, M. A. (2021). Suicide and suicidal behaviors in the context of covid-19 pandemic in bangladesh: a systematic review. *Psychology Research and Behavior Management*, *14*, 695.

McEwen, B. S., & Gianaros, P. J. (2011). Stress-and allostasis-induced brain plasticity. *Annual Review of Medicine*, *62*, 431–445.

Mertens, G., Gerritsen, L., Duijndam, S., Salemink, E., & Engelhard, I. M. (2020). Fear of the coronavirus (covid-19): Predictors in an online study conducted in march 2020. *Journal of Anxiety Disorders*, *74*, 102258.

Meule, A. (2017). Reporting and interpreting task performance in go/no-go affective shifting tasks. *Frontiers in Psychology*, *8*, 701.

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology*, *41*(1), 49–100.

Moore, A., & Malinowski, P. (2009). Meditation, mindfulness and cognitive flexibility. *Consciousness and Cognition*, *18*(1), 176–186.

Morse, D. R., Martin, J. S., Furst, M. L., & Dubin, L. L. (1977). A physiological and subjective evaluation of meditation, hypnosis, and relaxation. *Psychosomatic Medicine*, *39*(5), 304–324.

Mrazek, M. D., Mooneyham, B. W., & Schooler, J. W. (2014). Insights from quiet minds: the converging fields of mindfulness and mind-wandering. *Meditation–Neuroscientific Approaches and Philosophical Implications*, 227–241.

Pelletier, K. R. (1977). *Mind as healer, mind as slayer: A holistic approach to preventing stress disorders.* Dell.

Perich, T., Manicavasagar, V., Mitchell, P. B., & Ball, J. R. (2013). The association between meditation practice and treatment outcome in mindfulness-based cognitive therapy for bipolar disorder. *Behaviour Research and Therapy*, *51*(7), 338–343.

Peterson, R. L., Boada, R., McGrath, L. M., Willcutt, E. G., Olson, R. K., & Pennington, B. F. (2017). Cognitive prediction of reading, math, and attention: Shared and unique influences. *Journal of Learning Disabilities*, *50*(4), 408–421.

Phneah, S. W., & Nisar, H. (2017). Eeg-based alpha neurofeedback training for mood enhancement. *Australasian Physical & Engineering Sciences in Medicine*, *40*, 325–336.

Raffone, A., & Srinivasan, N. (2017). *Mindfulness and cognitive functions: Toward a unifying neurocognitive framework* (Vol. 8). Springer.

Rathee, S., Bhatia, D., Punia, V., & Singh, R. (2020). Peak alpha frequency in relation to cognitive performance. *Journal of Neurosciences in Rural Practice*, *11*(03), 416–419.

Rees, B. L. (1995). Effect of relaxation with guided imagery on anxiety, depression, and self-esteem in primiparas. *Journal of Holistic Nursing*, *13*(3), 255–267.

Ruedy, N. E., & Schweitzer, M. E. (2010). In the moment: The effect of mindfulness on ethical decision making. *Journal of Business Ethics*, *95*, 73–87.

Rydzewska, K., Rusanowska, M., Krejtz, I., & Sedek, G. (2017, 01). *Uncontrollability in the classroom: The intellectual helplessness perspective.*

Sabatinelli, D., Lang, P. J., Bradley, M. M., & Flaisch, T. (2006). The neural basis of narrative imagery: emotion and action. *Progress in Brain Research*, *156*, 93–103.

Schmertz, S. K. (2006). The relation between self-report mindfulness and performance on tasks of attention.

Scholz, U., La Marca, R., Nater, U. M., Aberle, I., Ehlert, U., Hornung, R., ... Kliegel, M. (2009). Go no-go performance under psychosocial stress: Beneficial effects of implementation intentions. *Neurobiology of Learning and Memory*, *91*(1), 89–92.

Scotland-Coogan, D., & Davis, E. (2016). Relaxation techniques for trauma. *Journal of Evidence-Informed Social Work*, *13*(5), 434–441.

Shafer, K. C., & Greenfield, F. (2000). *Asthma free in 21 days: The breakthrough mind-body healing program*. Harper San Francisco.

Shapiro, D. A., & Shapiro, D. (1982). Meta-analysis of comparative therapy outcome studies: a replication and refinement. *Psychological Bulletin*, *92*(3), 581.

Shapiro, S. L. (2009). The integration of mindfulness and psychology. *Journal of Clinical Psychology*, *65*(6), 555–560.

Simonton, O. C., & Matthews-Simonton, S. (1981). Cancer and stress counselling the cancer patient. *Medical Journal of Australia*, *1*(13), 679–683.

Simonton, O. C., Matthews-Simonton, S., & Sparks, T. F. (1980). Psychological intervention in the treatment of cancer. *Psychosomatics*, *21*(3), 226–233.

Singh, B., & Pandey, S. (n.d.). *Spiritual healing and rajyoga meditation in schizo-affective disorder, depressive type-a case report.*

Spielberger, C. D. (1983). *State-trait anxiety inventory for adults.*

Stapleton, P., Dispenza, J., McGill, S., Sabot, D., Peach, M., & Raynor, D. (2020). Large effects of brief meditation intervention on eeg spectra in meditation novices. *IBRO Reports*, *9*, 290–301.

Stevens, C., & Bavelier, D. (2012). The role of selective attention on academic foundations: A cognitive neuroscience perspective. *Developmental Cognitive Neuroscience*, *2*, S30–S48.

Sung, B., Roussanov, O., Nagubandi, M., & Golden, L. (2000). A002: Effectiveness of various relaxation techniques in lowering blood pressure associated with mental stress. *American Journal of Hypertension*, *13*(S2), 185A.

Tang, Y.-Y., Lu, Q., Feng, H., Tang, R., & Posner, M. I. (2015). Short-term meditation increases blood flow in anterior cingulate cortex and insula. *Frontiers in Psychology*, *6*, 212.

Tang, Y.-Y., Ma, Y., Wang, J., Fan, Y., Feng, S., Lu, Q., ... others (2007). Short-term meditation training improves attention and self-regulation. *Proceedings of the National Academy of Sciences*, *104*(43), 17152–17156.

Tang, Y.-Y., Posner, M. I., & Rothbart, M. K. (2014). Meditation improves self-regulation over the life span. *Annals of the New York Academy of Sciences*, *1307*(1), 104–111.

Thomas, K. M., & Sethares, K. A. (2010). Is guided imagery effective in reducing pain and anxiety in the postoperative total joint arthroplasty patient? *Orthopaedic Nursing*, *29*(6), 393–399.

Titz, C., & Karbach, J. (2014). Working memory and executive functions: effects of training on academic achievement. *Psychological Research*, *78*, 852–868.

Trautwein, F.-M., Kanske, P., Böckler, A., & Singer, T. (2020). Differential benefits of mental training types for attention, compassion, and theory of mind. *Cognition*, *194*, 104039.

Vines, S. W. (1994). Relaxation with guided imagery: effects on employees' psychological distress and health seeking behaviors. *AAOHN Journal*, *42*(5), 206–213.

Vøllestad, J., Nielsen, M. B., & Nielsen, G. H. (2012). Mindfulness-and acceptance-based interventions for anxiety disorders: A systematic review and meta-analysis. *British Journal of Clinical Psychology*, *51*(3), 239–260.

Wada, Y., Takizawa, Y., Zheng-Yan, J., & Yamaguchi, N. (1994). Gender differences in quantitative eeg at rest and during photic stimulation in normal young adults. *Clinical Electroencephalography*, *25*(2), 81–85.

Williams, J. M. G., Crane, C., Barnhofer, T., Brennan, K., Duggan, D. S., Fennell, M. J., ... others (2014). Mindfulness-based cognitive therapy for preventing relapse in recurrent depression: a randomized dismantling trial. *Journal of Consulting and Clinical Psychology*, *82*(2), 275.

Wirga, M., & DeBernardi, M. (2002). The abcs of cognition, emotion, and action. *Archives of Psychiatry and Psychotherapy*, *4*(1), 5–16.

Wójcik, G. M., Kawiak, A., Kwasniewicz, L., Schneider, P., & Masiak, J. (2019). Azure machine learning tools efficiency in the electroencephalographic signal p300 standard and target responses classification. *Bio-Algorithms and Med-Systems*, *15*(3).

Zeidan, F., Johnson, S. K., Diamond, B. J., David, Z., & Goolkasian, P. (2010). Mindfulness meditation improves cognition: Evidence of brief mental training. *Consciousness and Cognition*, *19*(2), 597–605.

Zemla, K., Sedek, G., Wróbel, K., Postepski, F., & Wojcik, G. M. (2023). Investigating the impact of guided imagery on stress, brain functions, and attention: A randomized trial. *Sensors*, *23*(13), 6210.