Comparison of psychophysiological and behavioral predictors of training effects with a complex task in the form of a strategic computer game.

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Podziękowania

Lista osób, którym chciałabym podziękować za ich pomoc, cierpliwość i wsparcie jest niesamowicie długa i gdybym miała wszystkie te osoby wymienić, z pewnością zajęłoby to kilka stron.

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Szczególne podziękowania kieruję do moich najbliższych – rodziny i przyjaciół, za wyrozumiałość dla ciągłego niedoboru czasu, wsparcie w najtrudniejszych momentach, troskę i ogromną ilość wiary we mnie.

Abstract

Playing video games (VGs) is undoubtedly one of the most popular leisure activities today (Mazurkiewicz and Stefańska, 2021). Current reports indicate that approximately 3 billion people worldwide identify themselves as VG players. Besides being an economical and sociocultural phenomenon, VGs have also been discussed in the context of their potential consequences on cognitive skills (e.g., Franceschini et al., 2013; Green and Bavelier, 2003).

The cumulative evidence suggests that action VG players outperform non-players in several cognitive tasks measuring such skills as visual attention, some aspects of cognitive control, general processing speed, and working memory (e.g., Colzato et al., 2013; Green and Bavelier, 2007). Additionally, according to recent investigations, even relatively short training in action VGs improves subjects' performance in a subsequent cognitive examination (e.g., Basak et al., 2008).

This aspect of VG playing seems to be particularly interesting. In the light of recent meta-analyses (e.g., Dougherty et al., 2016; Guye and von Bastian, 2017; Melby-Lervåg et al., 2016; Sala and Gobet, 2019), traditional cognitive-training programs seemingly bring few benefits and have minimal effect on domain-general cognitive skills. Consequently, it comes as no surprise that VGs have begun to be considered as a tool in cognitive training, and therefore used to maintain or even increase a person’s cognitive abilities. On the other hand, knowledge about the relationship between playing VGs and cognitive functioning can be beneficial to the e-sport community, to assess the predisposition and development of players or to build effective training systems.

My research project aimed to answer the question of whether cognitive training, using a Real-Time strategy (RTS) game as a training tool, can have a positive impact on participants’ cognitive functioning and their neural indicators (ERP and oscillations). What is more, I wanted to test whether an applied training model (rigid versus changing environment) would differentiate its impact on cognition. Such a comparison offers deeper insight into the significance of the applied training model. It is important to mention that this topic is often overlooked in VG research, although it may be no less important than the type of game used and the duration of the applied training. Finally, I wanted to investigate whether the initial, neurophysiological and/or behavioural indexes can serve as effective predictors of procedural learning and cognitive flexibility during complex skill acquisition. All of the aforementioned features of the study design were aimed to test the two-way relationship between video game playing and cognitive functioning

Hence, in my project I focused on data collected from participants who declared themselves as non-gamers and took part in a longitudinal training study. Participants were divided into a control group (CG) and two training groups that differed in the complexity of the training environment: fixed (FEG) and variable (VEG), with the second being more challenging. Both training groups played an RTS game - StarCraft II - for 30 hours over the course of approximately 4 weeks. EEG and behavioral data gathering were conducted before and after the onset of training (or after the period of 4 weeks for the CG) within the change detection and the attentional blink paradigms, which measure VWM capacity and the temporal limits of attention. What is important, the analysis covered the telemetric data obtained during 30 hours of gaming, which allowed me to observe the process of acquiring new skills required in the game and determine the level of advancement of individual participants.

Analyses of the data from the attentional blink task revealed that both FEG and VEG participants were able to significantly improve their behavioral results, with no differences between groups. However, significant differences appeared in the psychophysiological indicators of task performance. VEG participants increased their P300 amplitude power in the post-training measurement, while the P300 of FEG participants decreased. What is more, in the VEG sample, the amplitude of the P300 component (which is related to conscious visual perception) in the pre-training session appeared to be predictive of the level of achievement in the game. In the case of the FEG sample, in-game behaviour appeared to be predictive of a training-related improvement in the AB task.

When it comes to the second cognitive task – the change detection task – two independent sets of analyses were conducted: the first focused on the CDA (Contralateral Delay Activity) component and behavioral index of memory capacity (K-value), the second – focusing on alpha and theta oscillations.

The first study showed that working memory capacity (K calculated according to Pashler's (1988) formula) increased after training in both training groups, but not in the control group. What is more, I found that in-game achievements could be predicted by looking at the psychophysiological indices (CDA amplitude) recorded at the pre-training measurement, but only in the VEG sample. Then again, the obtained results suggested that the strength of the psychophysiological indicator – this time of VWM capacity - might be a marker of future success in video game acquisition.

Further analyses taking into account the oscillatory EEG activity and more sophisticated telemetric variables indexing subject's in- game behavior revealed that initial behavioral (K) and neurophysiological (alpha and theta power) indicators could predict the level of proficiency that participants achieved during training. Higher levels of the initial alpha power and lower levels of initial theta power were associated with greater in-game results. Interestingly, these effects were stronger for VEG participants with significantly higher in-game advancement.

The results of my research show that playing an RTS game can have a positive impact on select cognitive functions. Upon closer examination, it turned out that the unique positive effects were stronger in the group with more complex training models, showing the important role of not only "what game are we playing?", or "for how long?", but also "how we're playing?". Lastly, the obtained results suggest not only that differences in the neurophysiological response might be treated as a marker of future success in video game acquisition, but also that in-game achievements may later be reflected in better behavioral outcomes.

Streszczenie

Gry komputerowe od drugiej połowy XX wieku cieszą się niesłabnącą popularnością, a aktualne raporty wskazują na to, że już ponad 3 miliardy osób na świecie identyfikuje się jako gracze. Stały się one jednak nie tylko fenomenem kulturowym i gospodarczym. Na przestrzeni ostatnich kilku dekad coraz częściej poruszany jest ich potencjalny wpływ na funkcje poznawcze użytkowników (np. Franceschini et al., 2013; Green and Bavelier, 2003).

Istnieje szereg prac wskazujących na to, że zaawansowani gracze gier akcji, tj. osoby, które regularnie grały na przestrzeni przynajmniej 6 miesięcy od badania (Latham et al., 2013), osiągają wyższe wyniki – w porównaniu do osób niegrających – w testach mierzących takie funkcje poznawcze jak uwaga, przetwarzanie informacji, czy pamięć robocza (np. Colzato et al., 2013; Green and Bavelier, 2007). Co więcej, najnowsze badania wskazują na to, że nawet krótki okres grania może pozytywnie wpłynąć na nasze funkcjonowanie.

Badania te rzucają nowe światło na gry komputerowe i okazują się być interesujące na przynajmniej dwóch polach. Po pierwsze, aktualne metaanalizy (np. Dougherty i in., 2016; Guye i von Bastian, 2017; Melby-Lervåg i in., 2016; Sala i Gobet, 2019) wskazują, że tradycyjne treningi poznawcze nie przynoszą zamierzonych efektów w postaci długotrwałej poprawy ogólnego funkcjonowania poznawczego. Nie powinno więc dziwić, że gry komputerowe przykuły uwagę badaczy jako nowe, potencjalnie skuteczniejsze narzędzie treningu, który pozwoli na utrzymanie lub nawet poprawę poziomu wybranych funkcji poznawczy. Co więcej, temat związku pomiędzy funkcjonowaniem poznawczym i graniem w gry komputerowe wydaje się być szczególnie interesujący dla środowiska związanego z e-sportem. Poszerzenie wiedzy na ten temat i lepsze go zrozumienie może w przyszłości pomóc w lepszym określaniu predyspozycji graczy, monitorowaniu ich postępów, czy zarządzaniu treningiem tak, aby gracze mogli osiągać jak najlepsze wyniki w meczach.

Przeprowadzone przeze mnie badania miały pomóc w znalezieniu odpowiedzi na pytanie, czy trening poznawczy, wykorzystujący strategiczną grę komputerową czasu rzeczywistego (ang. Real-Time Strategy game; RTS) pozytywnie wpłynie na wybrane funkcje poznawcze osób badanych, co powinno znaleźć odzwierciedlenie w wyższych wynikach testów behawioralnych oraz ich neuronalnych korelatach. Co więcej, chciałam sprawdzić jak zaaplikowany model treningu wpłynie na uzyskane wyniki. Należy przy tym podkreślić, że większość aktualnych badań pomija szczegółowy opis rodzaju treningu, skupiając się częściej na rodzaju samej gry lub długości trwania treningu. Ostatnim z kluczowych dla mnie zagadnień, była próba zidentyfikowania neurofizjologicznych i/lub behawioralnych wskaźników, które mogłyby posłużyć jako predyktory pozwalające określić potencjał elastyczności poznawczej i – co za tym idzie – możliwość osiągnięcia wyższych wyników w grze. Wszystkie z omówionych aspektów miały na celu zaprezentowanie dwustronnej zależności występującej pomiędzy funkcjami poznawczymi a graniem w gry komputerowe.

W moich badaniach skupiłam się na danych pochodzących od osób, deklarujących się jako osoby niegrające, które wzięły udział w podłużnym badaniu treningowym. Finalnie uczestnicy badania zostali losowo przydzieleni do grupy kontrolnej (ang. Control group; CG) oraz dwóch grup trenujących: (1) trenujących w stałym (ang. Fixed Environment training Group; VEG) lub (2) w złożonym środowisku gry (ang. Variable Environment training Group; FEG). Obie grupy trenujące, na przestrzeni kolejnych 4 tygodni, spędziły 30 godzin rozgrywając mecze w grze RTS: StarCraft II. Dane behawioralne, wraz z rejestracją EEG,

zostały zebrane dwukrotnie: przed oraz po zakończeniu treningu (lub w odstępie 4 tygodni – w przypadku grupy kontrolnej). W trakcie pomiarów, uczestnicy wykonywali dwa testy poznawcze: Change Detection (CD) oraz Attentional Blink (AB), które pozwalają na pomiar pojemności wzrokowej pamięci roboczej (ang. Visual Working Memory; VWM) oraz czasowych granic uwagi. Dodatkowo, przeanalizowane zostały dane telemetryczne, pochodzące z 30 godzin gier. Pozwoliło to na szczegółowy wgląd w proces nabywania poszczególnych umiejętności w grze oraz ocenianie poziomu zaawansowania osób badanych.

Analiza danych pochodzących z zadania AB, podczas której skupiam się na grupach trenujących, wykazała, że obie grupy były w stanie istotnie zwiększyć poprawność wykonania zadania. Choć różnice pomiędzy grupami nie występowały na poziomie behawioralnym, grupy okazały się istotnie różnić na poziomie neurofizjologicznym. Podczas gdy w grupie VEG amplituda komponentu P300 okazała się zwiększyć po treningu, w przypadku FEG zmalała. Co więcej, komponent P300, zarejestrowany w trakcie pierwszego pomiaru, okazał się skutecznie przewidywać liczbę rozegranych przez graczy w grupie VEG meczy na wysokich poziomach trudności. Z drugiej strony, wskaźniki pochodzące z gry w grupie FEG skutecznie przewidywały poprawę (lub pogorszenie) wyników behawioralnych.

Analiza danych pochodzących z zadania CD podzielona została na dwa etapy. W pierwszej kolejności skupiłam się na potencjale wywołanym CDA oraz behawioralnym wskaźniku pojemności wzrokowej pamięci roboczej – K. W trakcie drugiego etapu, analizie poddane zostały dodatkowo fale alfa i theta.

Pierwsza część analiz wykazała, że pojemność wzrokowej pamięci roboczej (wyrażona przez K wyliczone za pomocą formuły Pashlera (1998)) istotnie wzrosła w grupach trenujących, ale nie grupie kontrolnej. Analizy wykazały również, że amplituda CDA pochodząca z pierwszego pomiaru pozwala przewidzieć finalną liczbę rozegranych przez uczestnika badania meczy (co jest ściśle związane z ogólnym poziomem zaawansowania). Podobnie, średni czas stworzenia pierwszej jednostki atakującej skutecznie przewidywał wartość K, którą gracz miał otrzymać w drugim pomiarze. Uzyskane wyniki, podobnie do wyników uzyskanych z zadania AB, pokazały, że neurofizjologiczne korelaty funkcji poznawczych potrafią skutecznie wskazywać graczy o wyższym potencjale.

W ostatniej z przeprowadzonych serii analiz wykazałam, że wskaźniki behawioralne (K) oraz neurofizjologiczne (moc fali alfa oraz theta) skutecznie przewidują kolejne, bardziej szczegółowe zmienne z gry. Co istotne, wyniki te okazały się być silniejsze w grupie VEG, która ogólnie charakteryzowała się wyższymi osiągnięciami w grze, w porównaniu do FEG. Kolejny raz, podkreśla to jak istotnym aspektem rozwoju jest odpowiednio wymagające i złożone środowisko treningu, a co za tym idzie, gry.

Przeprowadzone przeze mnie badania wskazują na to, że gry typu RTS faktycznie mogą wywierać pozytywny wpływ na wybrane funkcje poznawcze. Co warte podkreślenia, rodzaj zaaplikowanego treningu, okazał się jednym z kluczowych czynników, co jasno wskazuje na to, że nie tylko rodzaj gry i długość odbytego treningu, ale też sposób i środowisko, w jakim grają osoby badane, wpływają na siłę lub nawet wystąpienie danego efektu. Ostatecznie, uzyskane wyniki sugerują, że nie tylko możliwe jest przewidywanie sukcesów w grze na podstawie neurofizjologicznych i behawioralnych wskaźników danych funkcji poznawczych, ale też zmienne pochodzące ze środowiska w grze mogą przewidywać poziom wyniku w danym teście poznawczym. Wszystko to dowodzi istnienia dwustronnej relacji pomiędzy grami, a poszczególnymi funkcjami poznawczym.

Table of Contents

Introduction 1
Different types of VGs 1
Importance of computer science methods in in-game performance understanding........ 3
Individual predispositions 4
Attentional blink phenomenon and RTS games 4
Visual Working Memory and RTS games 5
Purpose of presented studies 6
Research questions........ 7
Research presentation 7
Experimental Task 1 – Attentional Blink paradigm........ 8
Experimental Task 2 – Change detection paradigm 8
Training models........ 9
Results 10
In-game achievements 10
Result obtained from the Attentional Blink task........12
Result obtained from the Change detection task 13
Contribution and innovation........15
Discussion........16
References........18
Scientific Profile of the Candidate........23
Manuscripts comprising the thesis........26
The role of individual differences in attentional blink phenomenon and real-time-strategy game proficiency 27
Authors' contributions........39
Psychophysiological, but Not Behavioral, Indicator of Working Memory Capacity Predicts Video Game Proficiency........52
Authors' contributions........63
Video game proficiency predicted by EEG oscillatory indexes of visual working memory. 74
Authors' contributions........121

Introduction

Playing video games (VGs) is undoubtedly one of the most popular leisure activities today (Mazurkiewicz and Stefańska, 2021). However, besides being an engaging form of entertainment, playing video games has also been recently discussed in the context of its potential consequences on attentional and perceptual skills (e.g., Bavelier et al., 2011; Franceschini et al., 2013; Green and Bavelier, 2003). Particularly, video games defined as "action video games" are thought to exert a significant influence on human cognitive functioning. According to Green and Bavelier (2003), VGs that can be classified to this category need to: "have fast motion, require vigilant monitoring of the visual periphery, and often require simultaneous tracking of multiple targets."

In fact, the cumulative evidence suggests that action VG players outperform non-players in several cognitive tasks measuring such skills as visual attention, some aspects of cognitive control, general processing speed, and working memory (e.g., Blacker and Curby, 2013; Castel et al., 2005; Colzato et al., 2013; Dye et al., 2009; Green and `, 2003, Green and Bavelier, 2006, Green and Bavelier, 2007; Strobach et al., 2012). What is more, according to recent investigations, even relatively short training in action VGs (e.g., 10 h) can improve subjects' performance in a subsequent cognitive examination (e.g., Basak et al., 2008; Feng et al., 2007).

In the light of recent meta-analyses (e.g., Dougherty et al., 2016; Guye and von Bastian, 2017; Melby-Lervåg et al., 2016; Sala and Gobet, 2019) indicating that traditional cognitive-training programs (e.g. Jaeggi et al., 2010) bring few benefits and have a minimal effect on domain-general cognitive skills, it comes as no surprise that VGs have started to be seen as a potentially promising new tool for enhancing cognitive skills. The resemblance of game environments and their dynamics to real-world complexity - as well as their inherently motivating character - are currently considered as their greatest assets, with potential applications in the process of both restoring cognitive functions following brain impairments and in preventive cognitive interventions.

Different types of VGs

While there are many different types of VGs, the particular category called action video games (AVGs) has gained substantial research interest. While the definition of AVGs is broad and differs in the scientific and commercial contexts, its subcategories are easier to identify.

First-person shooter (FPS) is commonly mentioned as the most popular sub-genre of AVGs. FPS games are played from the first-person perspective of a single protagonist. The main goal of the game is usually to fight enemies while navigating through a three-dimensional world. Players must rapidly adjust to changes in weapons, environments, and enemy characteristics as each of these can require specific strategies and handling.

On the other hand, Real-time strategies (RTS) are less commonly listed as a sub-category of AVGs, presenting them as a completely separate type of game that can also have a strong influence on players' cognitive functioning. In these games, players are playing from a top-down (allocentric) perspective. RTS games require that players manage a host of units and buildings placed within an expansive environment.

Games of this type are typically comprised of three separate tasks that must be managed simultaneously: gathering resources (by assigning units to do so), spending the resources to create units (which vary in terms of cost to create and abilities), and directing fighting units in battle against the enemy (Colzato et al., 2010; Dobrowolski et al., 2015).

In the presented study, StarCraft II (SC2) - which is considered as one of the most genre defining RTS games – was used. The central objective of the game is to defeat opponents by overpowering them, usually by destroying all of their buildings. The literature suggests that SC2 is a cognitively demanding game that involves specialized skills, such as rapid visual information processing, performing missions with precision in time, left and right-hand coordination, and transforming mental plans into motor movements (Glass et al., 2013; Thompson et al., 2017). What is more, SC2 is very popular among RTS players, who compete with each other not only at the amateur level, but also at the professional level during official tournaments. The usage of a commercial game (unlike games created solely for research purposes) allows us to extend the obtained results to the actual population of RTS players and to later compare them with the results obtained by RTS experts. Above all, SC2 provides the opportunity to rewatch played matches and to extract telemetric data, thanks to which it is possible to analyse in-game indicators such as Perception Action Cycles (where one PAC begins with an attentional switch and ends with the next attentional switch), Actions Per Minute, or hotkeys usage, which may reflect the improvement of cognitive and motor skills in the game.

Figure 1 | First-person perspective of an expert SC2 player during the match. To watch the full clip, see: http://y2u.be/bexWuHmV32A.

Importance of computer science methods in in-game performance understanding

As mentioned, SC2 offers the ability to extract individual performance indicators, which gives a better insight into in-game performance. Although the analysis of telemetric data is still not popular in neurocognitive research, it is widely used in computer science. Telemetric data are constantly analyzed in order to improve the construction of AI applied in the game itself. On the other hand, professional players or teams' coaches seem to be very interested in this subject and use SC2 indicators to analyze and rate player performance.

Thanks to machine learning methods, it is possible to build models that distinguish key moments in the game, players' strategies, and overall in-game statistics, which - thanks to further analysis - can be identified as crucial in terms of winning the match (Białecki et al., 2021; Huang et al., 2017). The need to understand in-game behavior has come to the level where there is a need to publish sets of matches themselves, which can be later used as a training base in machine learning processes (Białecki et al., 2022).

Therefore, it is important to mention that most of the available matches come from tournaments and professional players. There is still very little known about novice performance, whose results cannot be compared with those obtained from experts.

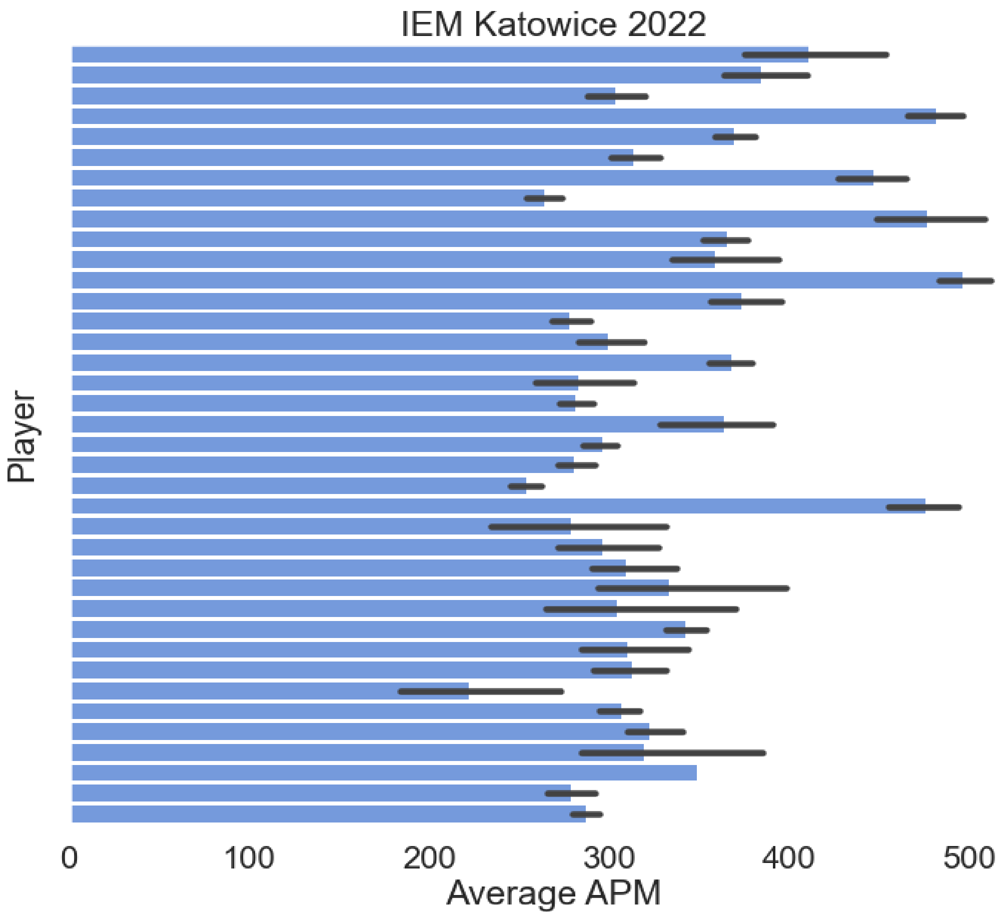

Figure 2 | Exemplary average Actions per Minute (APM) obtained from expert StarCraft II players. APM were extracted from matches played during the IEM Katowice 2022 tournament. For comparison, the participants whose data were collected in the presented study achieved an average of 25.94 APM (SD = 8.58).

Individual predispositions

Numerous investigations suggest the positive impact of video games on cognitive functioning based their evidence on comparisons between expert video gamers and non-gamers. Those studies are therefore correlational in nature. It is likely that the mechanisms through which playing certain video games influence cognitive functions are more complex, with multiple factors contributing to the observed differences. One such factor might be a self-selection effect, as it is possible that future video game experts demonstrate superior perceptual, attentional, and cognitive skills from the very beginning of their gaming adventure and these initial predispositions promote video game expertise (Boot et al., 2008, 2011). In fact, as demonstrated by Kramer and Erickson's research group (Erickson et al., 2010), variability in performance in demanding video games can be predicted from variations in the pretraining volume of the striatum. A similar pattern of results was found by Kowalczyk et al. (2020). These results seem to suggest that neuroanatomical differences can serve as effective predictors of procedural learning and cognitive flexibility during complex skill acquisition. What is more, similar effects have also been observed, for example, in the context of hippocampal volume and effectiveness of memory training (Engvig et al., 2012), and the value of such predictive models in the field of cognitive neuroscience has already been recognized (Gabrieli et al., 2015).

Such results can help to better assess the predisposition and development of potential professional players. However, this requires the creation of a universal, well-tested set of cognitive tests that can be linked with selected in-game performance.

Attentional blink phenomenon and RTS games

The attentional blink phenomenon is defined as a transitory impairment of attention appearing when multiple targets need to be processed in close temporal proximity. In laboratory settings this phenomenon is usually studied by a task described as rapid serial visual presentation (RSVP). The Attentional Blink task, originally presented by Raymond et al. (1992), described the RSVP paradigm as consisting of a series of stimuli which are displayed at a single location with a frequency of about 10 per second. In the stream of stimuli two are defined as targets. The second target (T2) is presented at various time lags following the first target (T1). Within this framework, the AB phenomenon manifests itself as the inability of subjects to report on the second target (T2) when it is presented between 200-500 ms after the first one (T1) (Kranczioch et al., 2003).

Invariant and stable as it seemed at first, in light of current investigations, the AB effect appears to be surprisingly susceptible to individual differences, with its magnitude varying from one individual to another (Martens et al., 2006). What is more, as revealed by recent studies, certain experiences can attenuate the AB effect (review: Martens and Wyble, 2010). Frequent playing of action video games has been shown to be one such experience, with video game players outperforming non-video game players in detecting stimuli in the AB time window. The difference in performance between these two populations is thought to result either from faster target processing or increased ability to maintain several attentional windows in video-game players (Green and Bavelier, 2003; Oei and Patterson, 2014).

Despite numerous studies addressing factors influencing the AB phenomenon, its neurophysiological underpinnings are still a matter of debate. Recent studies seem to suggest, however, that targets presented in the AB time window can reach working memory, which is reflected at the neurophysiological level in the modulation of the P300 event-related potential (ERP or *event-related component*: ERC) (Kranczioch et al., 2003).

P300 peak latency varies from 250 to 650 ms after the stimulus. It is thought to represent the activity of the widespread frontoparietal networks and to be related to engagement of attentional resources and working memory processes, which are both crucial for dealing with cognitive tasks (Bonala and Jansen, 2012). In the studies employing the AB paradigm, the P300 component, in contrast to earlier ERP components such as P1 or N1, has been shown to be evoked only by targets which were detected during the blink interval (Sergent et al., 2005; Sessa et al., 2007). As Kranczioch et al. suggested, such results can be interpreted as evidence that relevant information presented during the AB time window is not entirely lost, but on the contrary, in some trials can be compared with templates held in working memory. In the light of those investigations, the P300 component might be considered as a marker indicating the depth of information processing. However, to the best of my knowledge its role in marking post-training changes in stimuli processing in the AB task has not yet been investigated.

Visual Working Memory and RTS games

Visual working memory (VWM) allows us to maintain visual information over short periods of time for manipulation or later access (Baddeley, 2003; D'Esposito and Postle, 2015). VWM is an important cognitive function in our daily life and is essential for many higher-level cognitive processes, like problem-solving, learning by observation, or reading (Fukuda et al., 2010; Shipstead et al., 2012).

In the case of the current study, previous research showed that playing video games can enhance working memory performance, including VWM (Colzato et al., 2013; Oei and Patterson, 2014; Blacker et al., 2014). Playing VGs can also have a positive effect on visual short-term memory, as video game players have been shown to surpass non-video game players in remembering complex and intricate information (Blacker and Curby, 2013). However, it should be noted that there are also VG training studies in which no cognitive improvements were observed (Seçer and Satyen, 2014; Dominiak and Wiemeyer, 2016).

Previous research has relied on a well-established paradigm that measures VWM capacity: the change detection task (Luck and Vogel, 1997, 2013). In this task, the participant maintains a visual image in memory over a short delay interval and answers if any item (or items) in a later probe image changed when compared to the sample image. The number of items presented (memory load) is manipulated, and performance (working memory capacity, an estimate of the number of items stored in WM measured by K calculated according to Pashler's formula) is compared between trials of different loads. Besides behavioural indicators, VWM can be measured by neurophysiological activity.

CDA is a negative slow-wave evoked component with an amplitude that relates to the number of objects maintained in VWM, so it could be interpreted as a neural index of WM load (Vogel and Machizawa, 2004; Luria et al., 2016). Previous research has shown that CDA amplitude is correlated with memory capacity (Vogel and Machizawa, 2004; Ikkai et al., 2010) and can be modified as a result of WM training. In this study, video games were used as a specific kind of cognitive training having the potential for VWM improvement.

What's more, previous studies have shown that neural oscillations, specifically alpha and theta bands, can also be identified as VWM indicators.

According to Klimesch, alpha oscillations (8-12 Hz) are involved with unrelated or/and competing information suppression and information selection for a given task, providing a sensory gating mechanism (Klimesch, 2012). Moreover, Klimesch indicates that alpha activity is associated with a specific type of encoding stage like early categorization and retrieval of information, which are related to the processing of any kind of meaningful information (Klimesch et al., 2011). In a review by Pavlov and Kotchoubey, the authors remarked that WM load (items kept in WM) influences alpha activity over the posterior areas of the brain. Therefore, it is important to mention that the directionality of such an effect differed across studies.

In addition to alpha, theta oscillations (usually classified within the 4 to 8 Hz range) have been related to WM processes. Studies focusing on humans have confirmed the relevance of theta activity to spatial navigation (Araújo et al., 1 2002; Kahana et al., 1999) and other cognitive processes, such as working memory (Raghavachari et al., 2001; Jensen and Tesche, 2002). Frontal-midline (FM) theta oscillations have been reported in many EEG studies during WM tasks of various task modalities (Onton et al., 2005; Gevins et al., 1997; Jensen and Tesche, 2002), where an increase in memory load is mostly correlated with an increase in FM theta power. However, some studies show this particular region to display an inverse relationship between theta power and VWM capacity (Brzezicka et al., 2019). Further, the oscillation corresponds not only to the memory load dictated by the task itself but also to the individual cognitive demand required to perform it (Zakrzewska and Brzezicka, 2014).

Purpose of presented studies

The aim of the presented series of articles was to examine the impact of the RTS games on players' cognitive functioning as measured by the attentional blink and change detection tasks. What is more, one of the main goals was to identify the neural and/or behavioral basis (and therefore – predictors) of being a good video-game player. Finally, the prepared articles covered the topics of the two-way relationship between RTS games and selected cognitive functions and the importance of the applied training models on achieving expected results.

Hence, in my project, I focused on data collected from participants who declared themselves as non-gamers and took part in a longitudinal training study. Participants were divided into a control group (CG) and two training groups that differed in the complexity of the training environment: fixed (FEG) and variable (VEG). Both training groups played StarCraft II for 30 hours across approximately 4 weeks. EEG and behavioural data gathering were conducted before and after the onset of training (or after the period of 4 weeks for the CG) within the change detection and the attentional blink paradigms, which measure VWM capacity and the temporal capacity limits of attention. Additionally, the analysis covered the telemetric data obtained from 30 hours of gaming, which allowed me to observe the process of acquiring new skills required in the game and determine the level of advancement of individual participants.

Research questions

1. Will cognitive training using an RTS game as a training tool have a positive impact on participants' cognitive functioning, and thus on the behavioral and/or neurophysiological results obtained in the attentional blink and the change detection tasks?
2. Will the obtained results differ depending on the group and the applied training model?
3. Are there behavioral and/or neurophysiological predictors that allow to identify players with higher predisposition to achieve better results in the RTS game?

Research presentation

104 participants in total were recruited online via a covert questionnaire from a total of 2472 applications. All participants reported normal or corrected-to-normal visual acuity, normal colour vision and normal hearing. They were right-handed and reported not being on any medications, no history of neurological or psychiatric disorders and injuries, including no previous head trauma, no previous head or neck surgery, and no brain tumours. All participants declared less than 5 hours of video games played per week over the past six months and no experience with action video games.

As a result of: (1) resignation, (2) faulty hardware configuration, (3) failure to meet all training objectives, (4) bad quality of data, and (5) lost data, between 42 (in the case of research focusing on Change Detection task – later refer as VWM) and 45 (in the case of research focusing on Attentional Blink task – later refer as AB) participants were excluded. All participants were randomly assigned to two training groups: Variable Environment training model (VEG) and Fixed Environment training model (FEG), and two control groups, which were later merged into one Control Group (CG). The detailed characteristics of the presented groups including demographic data and reasons for exclusion at individual stages of the study were described separately in the attached articles. The simplified study scheme, along with the analysed groups, is presented in Figure 3.

The research consisted of three steps:

(1) Pre-training measurement of cognitive functioning *via* Attentional Blink task (AB) and Change detection task (CD);

(2) 30 hours of training sessions applied to training groups; and

(3) Post-training measurement.

Experimenters were present during all meetings. Measurements and training sessions took place in the laboratories of the SWPS University in Warsaw.

To better understand the relationship between cognitive skills and in-game performance, besides behavioural data, I decided to focus on established neurophysiological indicators: P300 (see: *The role of individual differences in attentional blink phenomenon and real-time-strategy game proficiency*), contralateral delay activity (CDA) (see: *Psychophysiological, but Not Behavioral, Indicator of Working Memory Capacity Predicts Video Game Proficiency*) and neural oscillations in the theta and alpha frequency range (see: *Video game proficiency predicted by EEG oscillatory indexes of visual working memory*).

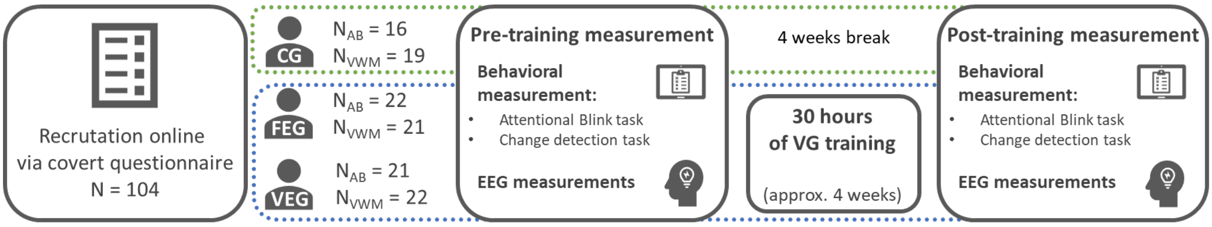

Figure 3 | Study design: Two measurement sessions were carried out during the study (pre-training and post-training). Training included 30 hours of playing a real-time strategy game (StarCraft II), spread out over 4 weeks. Training varied depending on the group. AB – Attentional Blink task, VWM – Visual Working Memory task (Change detection).

Experimental Task 1 – Attentional Blink paradigm

The experimental task used in the present study was based on the procedure outlined by Kranczioch et al. (2003). The task's specification was described in the attached article (see: *The role of individual differences in attentional blink phenomenon and real-time-strategy game proficiency*). The scheme of the exemplary trials is presented in Figure 4.

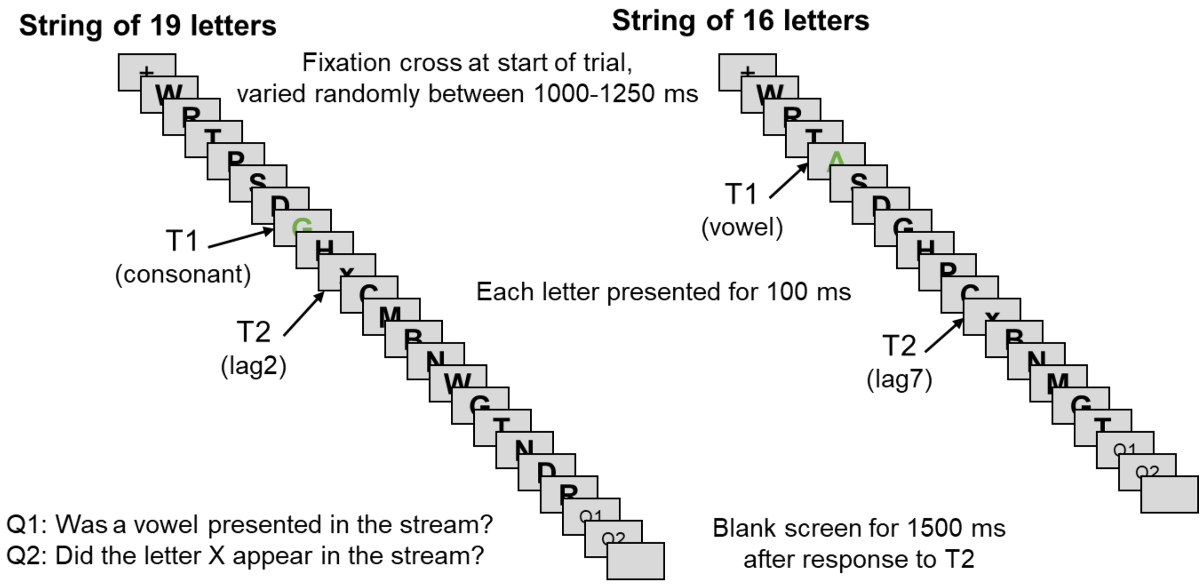

Figure 4 | Example of two trials of the Attentional blink task. The first trial consists of 19 letters. T1 is presented as a green letter G, and the "X" (T2) appears in Lag 2. The second trial consists of 16 letters, where T1 is presented as a green A letter, and "X" (T2) appears in Lag 7. Each trial started with a fixation cross after which a string of (16 or 19) letters was presented. Each letter was presented for 100 ms and then participants were asked about the type of T1 and the presence of T2. Each trial ended with a blank screen presented for 1500 ms after response to the second question.

Experimental Task 2 – Change detection paradigm

The experimental task was based on the procedure outlined by Vogel and Machizawa (2004). The task's specification was detailed in the attached article (see:

Psychophysiological, but Not Behavioral, Indicator of Working Memory Capacity Predicts Video Game Proficiency). The scheme of the exemplary trial is presented in Figure 5.

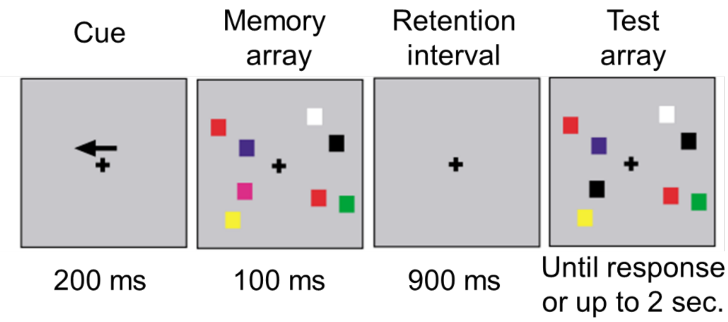

Figure 5. The change detection task. Participants directed their attention to a cued hemifield and compared two arrays of colored squares (memory and test arrays) separated by a retention interval. The test array was either identical to the memory array (no-change condition) or differed by one color (change condition). Participants answered whether the two arrays were identical or not.

Training models

Starcraft II is widely considered as the most challenging real-time strategy (RTS) game. The underlying challenges include a large observation space, a continuous and infinite action space, limited field of view, simultaneous moves for all players, and long-horizon delayed rewards for local decisions (Sun et al., 2018). Overall, the player is required to build a virtual base and army to attack and overcome their opponent. In 1 versus 1 matches, players need to focus on three main aspects of gameplay: (a) optimal resource gathering, (b) expanding, protecting, and engaging production potential, and (c) managing army composition and actions. (Kowalczyk et al., 2018)

SC2 gameplay is based on three playable races (Terran, Zerg, and Protoss), each of which has unique units and abilities and requires a different playstyle to optimize performance. Apart from the possibility of playing against other players, there are ten built-in levels of AI script difficulty for custom games: Very Easy, Easy, Medium, Hard, Harder, Very Hard, Elite, and three different Cheater options. In addition, five different AI strategies are available (1. Full rush, 2. Timing Attack, 3. Aggressive Push, 4. Economic Focus, 5. Straight to air). These strategies allow the AI to make high-level decisions so that it can attack the player in specific ways. The implemented difficulty levels and combat styles allow players to get to know a variety of gameplay possibilities and general game mechanics.

SC2 gives players the opportunity to re-watch their matches, which is commonly used to analyse their strengths and weaknesses. More importantly, thanks to tools such as sc2reader (a Python library), it is possible to extract telemetric variables presenting specific in-game achievements and performance. These data represent basic gameplay information (e.g. match length, match result, information about the players), typical game indicators like APM (Actions per minute), PACs (Perception Action Cycles; refers to number of independent map areas at which actions are performed), PAC latency (latency to first action in a PAC), usage of hotkeys (keyboard shortcuts to certain actions), and also specific economic data (e.g. the amount of gathered/spent resources), key events (e.g. creation or loss of key buildings and units), and the specific time at which individual actions and events took place. Knowing the values of individual telemetric variables and the rules that are applied in the game, it is possible to draw objective conclusions about the level of a player's advancement.

In the present study, SC2 training was divided into a four-week period, with a total of 30 hours of gameplay. This training entailed playing SC2 matches (approximately 20 minutes per match) against AI. As mentioned previously, the exact training experience depended on the training group (FEG or VEG). The details are depicted in Figure 6.

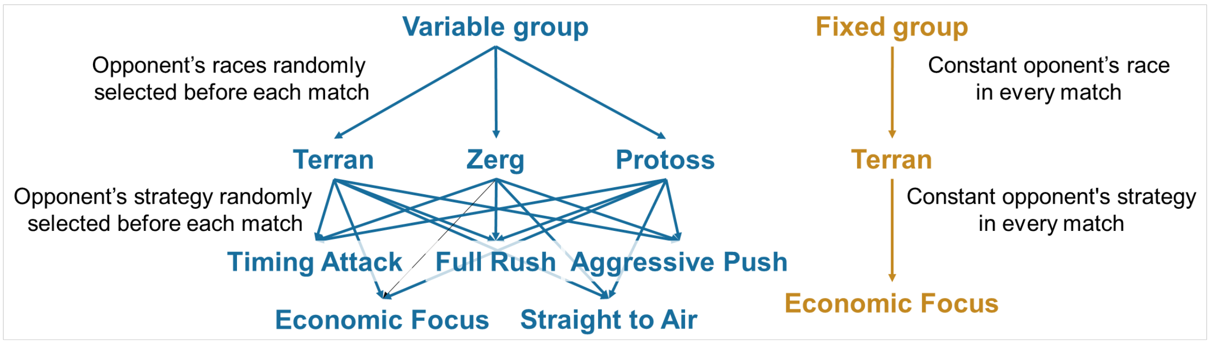

Figure 6. | All participants played the Terran faction during training. However, the strategy and race of the opponents varied according to the type of group. While Fixed Environment Group (FEG) always played against the Terran faction using the economic strategy, the Variable Environment Group (VEG) could match three factions, and each could use one of the five play strategies. The faction and strategy types were randomly assigned before each match in VEG.

Results

In relation to the first research question, both training groups significantly improved their behavioural results obtained in the attentional blink and change detection tasks. Importantly, a similar improvement was not observed in the CG, which was included in the change detection task analysis. Comparing the pre-training data to those obtained after the training, most of the analysed neurophysiological indicators of tested cognitive skills (excluding CDA) turned out to change significantly. Importantly, at the neurophysiological level, I observed opposing patterns of change, depending on the applied training model, and therefore group. Detailed analysis of the behavioural data from the change detection task showed that VEG was able to improve its results to a greater extent when compared to the other groups. Those results confirmed my expectation regarding the influence of the applied training model, raised by the second of the posted research questions.

Finally, the K value (behavioural indicator obtained from change detection task) and all of the measured neurophysiological indicators turned out to be able to correctly explain specific in-game achievements (third research question). Interestingly, most of the prepared models contained a predictor × group interaction, showing a stronger, significant effect in the VEG sample. This may show that FEG participants, despite having similar individual potential, did not have the opportunity to develop adequately in a less favourable, monotonous environment.

In-game achievements

In all of the studies that make up the presented series of articles, I undertook the analysis of the telemetric data obtained from the game environment. This made it possible to determine the final level of advancement of both: (1) individual players and (2) training groups.

During the analyses, I focused on both very general variables, such as the level of difficulty the player reached and the number of matches played at particular difficulty levels, but also on typical indicators for SC2 like APM and PAC, economic data, and key event latencies. Knowing the values of individual telemetric variables and the rules that are applied in the game, it was possible to draw objective conclusions about the level of a player's advancement.

First, the total time spent in the game and the mean number of matches played by each participant were calculated. Although there were no significant differences between the groups in the time spent playing SC2, participants from the VEG condition were able to play and win significantly more matches in that time period, which corresponds to significant differences between the length of played matches in the tested groups. It also stands in agreement with one of the most basic rules of SC2 players, stating that you can either lose the match for a long time or win it quickly.

Next, I focused on potential between-group differences based on variables indicated by logistic regression models. T-tests revealed that participants from the VEG condition had a significantly higher PAC latency, and a lower time of first army unit creation. What is more, VEG players were able to play significantly more matches on higher levels of difficulty.

Considering all that information, it seems clear that compared to FEG, VEG settings allowed non-gamer participants to be greatly proficient in SC2. Exemplary in-game indicators obtained by individual groups are presented in Figure 7.

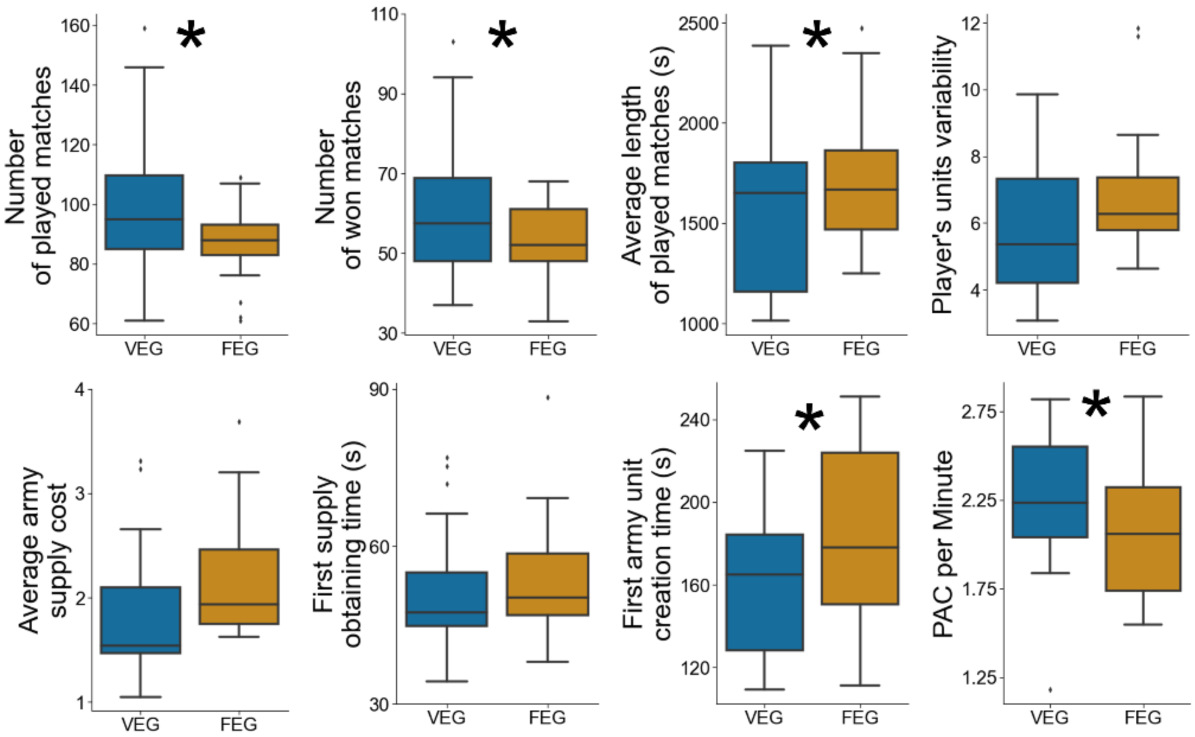

Figure 7 | The group comparison is presented on 8 telemetric variables, which were selected using logistic regression. The Variable Environment Group (VEG) was able to achieve significantly better in-game performance based on 5 of the presented variables than the Fixed Environment Group (FEG). Asterisks indicate significant differences ($p < 0.05$).

Result obtained from the Attentional Blink task

Analysis of the behavioural results allowed me to detect the AB effect on Lag 2. Further analysis revealed significant effects of Lag, Session and a significant Lag × Session interaction. While I did not observe any significant effect that included between-group differences, a detailed analysis showed that VEG participants were able to achieve slightly stronger improvement in comparison to FEG participants. The lack of significant behavioural between-group differences may be a result of the general high accuracy in the post-training measurement. Most importantly, the obtained results suggest that RTS games indeed enhance attentional skills, which can be measured by behavioural indicators, independently of the game variant being trained.

As the P300 component is associated with the conscious processing of stimuli, previous investigations have shown not only that the P300 component evokes as a result of item detection, but may also be significantly more positive in some Lag conditions in the AB task. I wanted to investigate if the positivity of P300, as a reaction to the visual stimuli, will increase after complex cognitive training, which should affect a number of cognitive skills involved in stimulus detection. Interestingly, while there were no significant main effects (like Lag or Session effects), the tested training groups presented opposite changes in the amplitude, which was measured during the post-training session. While VEG participants increased their P300 amplitude power in the post-training measurement, the P300 of FEG participants decreased, which resulted in a significant Session × Group interaction. The expected change was therefore observed in only one of the tested groups, which has undergone training with a higher level of complexity.

What is more, further analysis indicates that the stronger the initial P300 amplitude, the better the progress of participants in the game as measured by the number of matches played at the most difficult levels. Importantly, this effect was visible only in participants subjected to a varied training regimen. As the P300 ERP component is usually related to such cognitive processes as focusing attention or conscious processing and acting (Bonala and Jansen, 2012), its mean amplitude could correspond to each participant's individual cognitive resources in that field. On the other hand, the pre-session behavioural accuracy, contrary to psychophysiological indicators, seems not to be predictive of players' game achievement. It might indicate that neurophysiological reactions are more sensitive and accurate in pinpointing individual differences in cognitive capacities and therefore be related to the broader spectrum of tasks than behavioural results. Furthermore, the behaviour in the game environment appeared to be predictive of improvement in the AB task in the fixed environment game group. Specifically, participants who played more matches on the easiest levels of the game (which means they struggled to get higher and did not have a chance to practice more demanding actions) had worse improvement or even a decrease of accuracy in the AB task as measured by the difference between post-and pre-training sessions.

The main results are present in Figure 8.

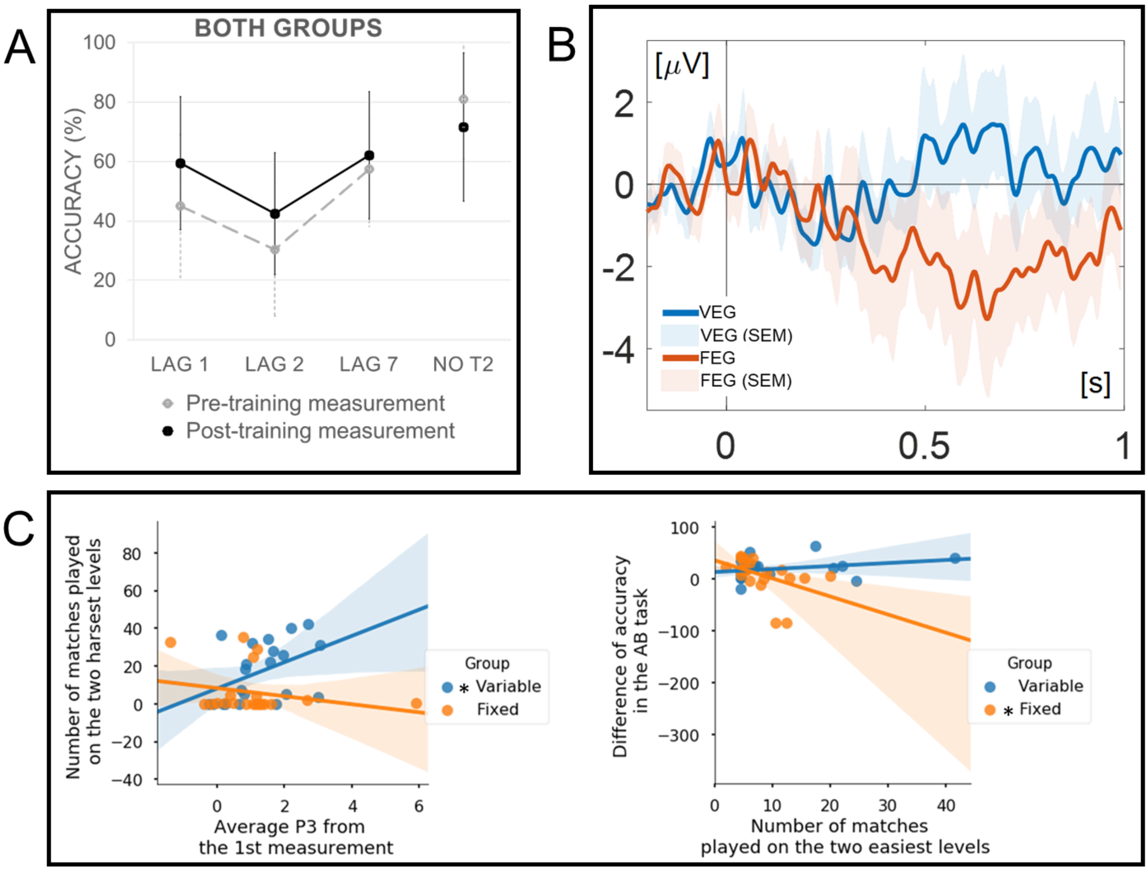

Figure 8 | (A) Comparison of accuracy from attentional blink task between sessions at every Lag and in No T2 appearance conditions. Both training groups were able to significantly increase their accuracy at Lag 1, Lag 2 and at NO T2 condition. **(B)** Differential waves (2nd measurement – 1st measurement) for each training group, with 0 point being T2 presentation moment. We can clearly observe opposite effects in amplitude change after training. (**C**) Exemplary significant moderation models obtained in the study.

Overall, the results suggest that the influence of RTS video games depends on the training model. While the aspects by which games could affect specific cognitive skills or how long it takes to induce such an effect, are widely discussed (e.g. Bediou et al., 2018), previous investigations in the field rarely pay attention to the usually limited gameplay and different training modes. Moreover, both the impact of the game and the game achievements may depend on the player's individual predispositions.

Result obtained from the Change detection task

Detailed analyses of VWM memory capacity, measured by the K values, revealed that the CG did not significantly increase its capacity of VWM at any of the used loads, FEG sample increased it at loads 4 and 5, while VEG sample was able to significantly increase it at every load. The exact results are presented in Figure 9. The obtained results show not only that RTS games can positively affect the capacity of VWM, but also that the applied training model may affect the strength of the obtained improvement.

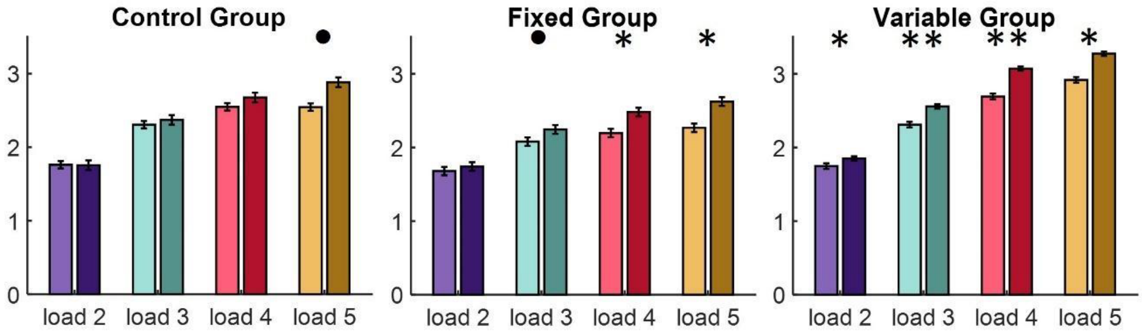

Figure 9 | The average K values for each set size in the two tests presented separately for each group. Lighter colors in the pair correspond to the pre-training measurement and darker to the post-training measurement. Asterisks indicate statistical significance: •p < 0.08, *p < 0.05, **p < 0.01.

All of the neurophysiological indicators of VWM (CDA, alpha and theta oscillations) revealed the main effect of Load. CDA turned out to also be correlated with the K value, which confirms its role as a neurophysiological indicator of VWM. While both of the tested oscillations turned out to change after the training process, analyses of the theta log power spectral density revealed that the obtained difference (increase in the power) was present only in VEG sample. The exemplary neurophysiological results are presented on Figure 10 and Figure 11.

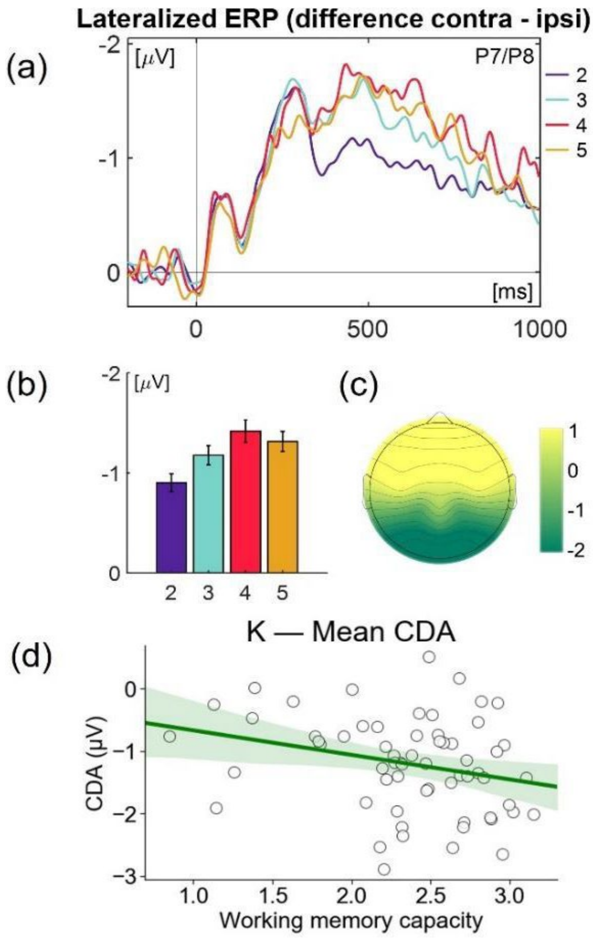

Figure 10 | (A) Grand average lateralized waveforms (contra—ipsi), averaged across P7/P8 electrodes, separately for all lateralized target distributions. For statistical analyses of CDA, the mean amplitude from 400 to 900 ms was used. **(B)** Mean CDA amplitude from 400 to 900 ms, separately for each load. Error bars denote standard errors of the mean, corrected for within-subjects comparisons. **(C)** Topography of the average activity at each electrode site from 400 to 900 ms. As values were averaged across paired electrodes, the topography is perfectly symmetrical. **(D)** Scatterplot of working memory capacity (K) averaged across loads and contralateral delay activity (CDA) averaged across loads

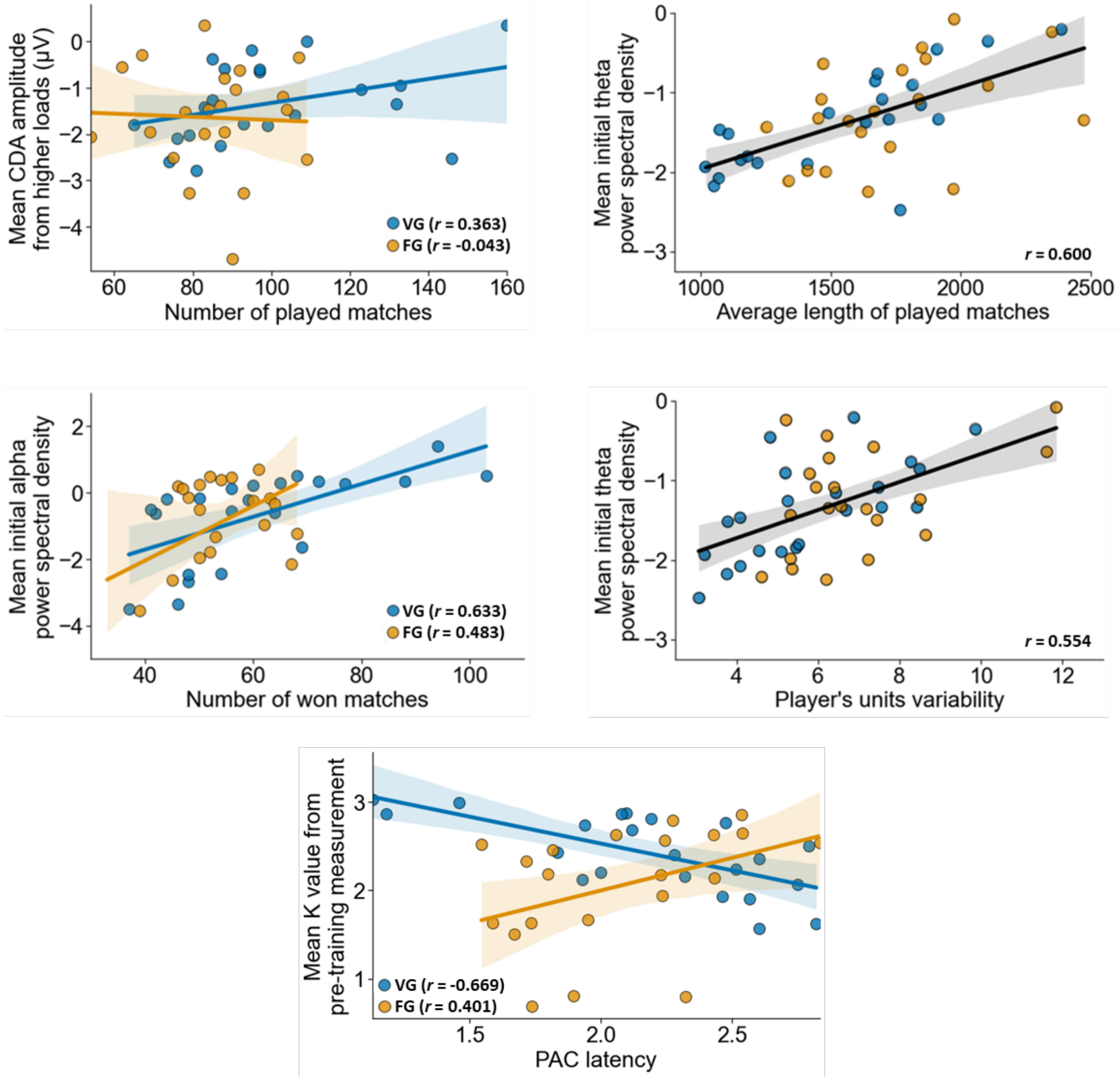

Figure 11 | Exemplary scatterplots showing the relationship between the behavioral and neurophysiological (CDA and oscillatory EEG activity) indicators of VWM and selected telemetric variables. Blue markers refer to VEG and orange markers refer to FEG.

Contribution and innovation

The main contribution in the domain of **Psychology** is in the areas of **Cognitive Psychology** and **Cognitive Neuroscience**. In the prepared articles, I analyze in depth the possible effects of VG playing on visual working memory and attentional processes. My research focuses on replicating well documented results. On the other hand, I focus on frequently overlooked factors such as the type of applied training model or participants' individual predispositions. In my research, I address relevant methodological problems, such as proper selection of the research sample, training structure, and objective methods of evaluating training effects.

Therefore, I applied **Computer Science** methods to extract, select, and analyze in-game indicators that shed new light on the effectiveness of the VG training. It is important to mention that such an approach is rarely used in Psychology, with the exception of research performed by Thompson et al. (2014, 2017), who was the first to show that specific, detailed telemetric variables can be significantly correlated with select cognitive functions. What is more, presented the studies allowed us to build a database of matches obtained from novices. These are rare, hard-to-reach data that could allow us to better understand the skill learning process in SC2.

The obtained results may therefore turn out to be important both in the construction of cognitive training paradigms and in the construction of training paradigms designed to serve professional esports players. The prepared articles describing these topics in detail are attached to this dissertation in full.

Discussion

The presented research has expanded the existing knowledge about the relationship between the proficiency in RTS video games acquired during training and neurocognitive functioning. By analysing the data from a longitudinal training study, I showed that playing RTS games can positively affect select cognitive functions, such as VWM and selective attention.

Cognitive training using the RTS game as a tool turned out to have a positive influence on most of the examined behavioural and neurophysiological variables. Importantly, this impact seems to vary across applied training models, which made it possible to observe different results across two training groups.

The potential impact of VGs on cognitive functioning continues to be a topic of debate among researchers. Amongst studies showing the positive influence of playing VGs, there are numerous publications showing lack of similar effects (e.g., Irons et al., 2011; Murphy and Spencer, 2009). The results obtained in the present studies may explain that divergence. While recent studies accurately describe the type and duration of applied video game training, the exact type of training (with detailed parameters used to define the game environment) is rarely explained. It turns out that not only the type of game or play time but also the way of playing has a key impact on the relationship between human cognitive abilities and actual in-game behaviour.

Apart from the game environment itself, difficulty level, complexity, and a mass of other variables that can be planned and coordinated by researchers, the analysis should also include in-game indicators, which allow us to assess whether the training is carried out in an appropriate manner. It goes without saying that aspects such as motivation and commitment to the training may be the key to its effectiveness. However, it should be emphasised that such factors are very difficult to measure, often related to self-described measures, and are most often completely ignored in similar studies. Adequate introduction to the training, observing and controlling of the players' gradual progress, and selecting the variables that are best in describing players' achievements could help to exclude participants who simply did not perform the training process properly or even to intervene during the training.

These important methodological issues, which have so far been largely ignored, may allow for greater consistency of the obtained results. What is more, this aspect can be crucial not only in trying to explain the potential impact of video games on human behaviour but also in extending the obtained results to a group of professional players.

Therefore, the results seem to be promising for advanced or even professional players looking to improve their in-game performance. Assuming that the relationship between video games and selected cognitive functions is two-sided, it is possible that adequate training, focusing on cognitive functions related to in-game performance, could improve player outcomes. From this perspective, the presented results are of potential interest to the esports community, pointing to the possibility of an alternative way of enhancing their abilities.

The playing of commercial video games and inspection of respective neural associations is a relatively novel research domain with a promising future. Nevertheless, this also implies a lack of the necessary findings to establish the outline of this domain. For this reason, I believe that my studies could guide research in future studies.

Therefore, it is important to mention that future investigations should examine a wider range of carefully selected tasks, which can contribute to creating a more complete spectrum of cognitive functions and the changes that they undergo through video game training. It may also be necessary to find their neurophysiological indicators, which may be more sensitive to small changes resulting from training. Then, video games should not be considered solely in terms of their popularity, the possibility of their application as a cognitive training tool in neurorehabilitation, or in terms of how they affect us, but also in terms of player's predispositions to achieve higher scores and methods of inspecting the training process.

Moreover, using more advanced statistical analyses, such as hierarchical linear models, could help to increase our knowledge of the relationship between EEG indicators and behavioural variables, both from the cognitive paradigms themselves and from more complex game environments. Similarly, the use of other machine learning methods to better select significant telemetric variables reflecting player behaviour or the strategies they adopt may also allow for presentation of a broader picture of the discussed relationships.

The inclusion of the data from the game environment in the analysis is undoubtedly still a novelty in the neurocognitive research field. However, in my research I tried to expand the knowledge about these variables as well as about their influence on the game, and possible connections with cognitive functions. During the research, I consequently applied increasingly accurate and objective methods of selecting variables that are best in reflecting players' advancement.

The lack of a sufficiently large control group and the small sample of active groups are also an unquestionable limitation. It should be emphasised that this limitation is largely due to drop-out, which is a common problem in longitudinal studies (e.g., Moore et al., 2017). What's more, the present project employed restrictive recruitment criteria, especially in terms of experience in video game playing, which finally resulted in an inability to e.g. re-complete the control groups. Further, all of the presented results are based solely on RTS training which - according to other studies - may require different cognitive functions and influence players differently when compared to FPS or TPS games. To be able to clearly understand the obtained results, they should also be compared to data and models built on professional - or at least more advanced - video game players from different types of video games.

Summarising the results of my research, I would like to emphasise how applicable and important this topic is. VGs are one of the most popular leisure activities in the present day. Over 65% of the US population plays VGs, and in the case of children and adolescents, this percentage even exceeds ninety percent. In addition to the undoubted cultural and economic impact, VGs also give hope for new methods of cognitive training, which can be used e.g. in neurorehabilitation processes. Esports is becoming a more and more entrenched field of sport, as it has faced new challenges in classifying the potential and development of their players. Beside all this, even if esports is not in our area of interest, or if we do not yet see the direct methods of VG application in neurorehabilitation, VGs are still gaining in popularity and seem to be an integral part of our lives - this alone should be a sufficient argument to want to understand how they affect us or our loved ones.

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Scientific Profile of the Candidate

Natalia Jakubowska

Google Scholar	https://scholar.google.com/citations?user=HI5reeYAAAAJ
Research Gate	https://www.researchgate.net/profile/Natalia-Jakubowska

Published articles:

Bramorska, A., Zarzycka, W., Żakowicz J., **Jakubowska, N.,** Balcerzak, B., Podolecka, W., Brzezicka, A., Kuć, K. (2022, 18th-20th May) How Diet Composition Correlates with Cognitive Functioning – Application of Principal Component Analysis (PCA) to Nutritional Data [Paper presentation]. AMIA 2022, online. DOI: 10.6084/m9.figshare.20066849 (**MNISW**: 140)

Kovbasiuk, A., **Jakubowska, N.**, Hryniewicz, N., Prusinowski, R., Brzezicka A., Kowalczyk-Grębska, N. (2021, 3rd-7th July) Cortical thickness as predictor of performance enhancement in complex real-time strategy game training [Paper presentation]. 30th Annual Computational Neuroscience Meeting, online. DOI: 10.1007/s10827-021-00801-9 (**IF**: 1.621, **MNISW**: 70)

Jakubowska N., Dobrowolski, P., Binkowska, A.A., Arslan, I.V., Myśliwiec, M., Brzezicka, A. (2021) Psychophysiological, but Not Behavioral, Indicator of Working Memory Capacity Predicts Video Game Proficiency, Frontiers in Human Neuroscience, 15. DOI: 10.3389/fnhum.2021.763821 (**MNISW**: 100; **IF**: 3.474)

Binkowska, A. A., **Jakubowska, N.**, Krystecka, K., Galant, N., Piotrowska-Cyplik, A., Brzezicka, A. (2021). Theta and Alpha Oscillatory Activity During Working Memory Maintenance in Long-Term Cannabis Users: The Importance of the Polydrug Use Context. Frontiers in Human Neuroscience, 15. DOI: 10.3389/fnhum.2021.740277 (**IF**: 3.474, **MNISW**: 100).

Binkowska, A. A., **Jakubowska, N.**, Gaca, M., Galant, N., Piotrowska-Cyplik, A., Brzezicka, A. (2021). Not Just a Pot: Visual Episodic Memory in Cannabis Users and Polydrug Cannabis Users: ROC and ERP Preliminary Investigation. *Frontiers in Human Neuroscience*, 15. DOI: 10.3389/fnhum.2021.677793 (**IF**: 3.474, **MNISW**: 100).

Jakubowska, N., Dobrowolski, P., Rutkowska, N., Skorko, M., Myśliwiec, M., Michalak, J., Brzezicka, A. (2021) The role of individual differences in attentional blink phenomenon and real-time-strategy game proficiency. Heliyon, 7(4). DOI: 10.1016/j.heliyon.2021.e06724 (**IF**: 3.776, **MNISW**: 40)

Unpublished articles (in review):

Jakubowska, N., Arslan, I.V., Chałatkiewicz, I., Dąbkowska, M., Podolecka, W., Brzezicka, A. Video game proficiency predicted by EEG oscillatory indexes of visual working memory. Article awaiting for reviews in *Frontiers in Psychology*. (**IF**: 4.232, **MNISW**: 70)

Okruszek, Ł., Rutkowska, N., **Jakubowska, N.** Communicative intentions automatically hold attention – evidence from event-related potential. Article awaiting for decision after the first round of reviews in *Social*

Neuroscience (**IF**: 2.381, **MNISW**: **100**)

Białecki, A., **Jakubowska, N.**, Dobrowolski, P., Krupiński, L., Białecki, P., Białecki, R., Gajewski, J. (2023, 1st May – 5th May) *SC2EGSet: StarCraft II Esporta Replay and Game-state Dataset.* Article awaiting for decision after reviews in ICLR 2023, Kigali, Rwanda (**MNISW**: 200).

Lewandowska, P., **Jakubowska, N.**, Hryniewicz, N., Prusinowski, R., Kossowski, B., Brzezicka, A., Kowalczyk-Grębska, N. Association between real-time strategy video game learning outcomes and pre-training brain white matter structure: preliminary study. Article awaiting for decision in *Scientific Reports* (**IF**: 4.996, **MNISW**: 140).

Selected conferences:

November 2021	**Aspect of Neuroscience** (Warsaw, PL) *Poster "Psychophysiological, but not behavioral indicators of VWM capacity predicts video game proficiency"* **(The Best Poster - Audience Award)**
December 2020	**NEURONUS** (Cracow, PL – conference online) *Poster "The role of individual differences in relation between RTS game proficiency and Attentional blink phenomenon"*
November 2019	**Aspects of Neuroscience** (Warsaw, PL) *Poster "Can training in strategic video game induce changes in neurocognitive functioning?"* **(Awarded as the best poster of the conference)**
October 2019	XIII Naukowa Sesja Doktorantów, SWPS University (Warsaw, PL) *Poster "Neurophysiological indicators of being a good e-player"* **(Awarded as the best poster of the conference)**
July 2019	**Salzburg Mind-Brain Annual Meeting** (Salzburg, AT) *Poster "The impact of training in RTS video game on the attentional blink phenomenon - an ERP study"*
June 2019	**Organization for Human Brain Mapping Annual Meeting** (Rome, IT) *Poster "The influence of the beliefs about the type of the second player in the Ultimatum Game: an ERP study"*
May 2019	**Cracow Cognitive Science Conference** (Cracow, PL) *Poster "Are video games capable of expanding one`s awareness?"* **(Awarded as the best poster of the conference)**
March 2019	**Cognitive Neuroscience Society Annual Meeting** (San Francisco, CA, USA) *Poster (1) "Working Memory "Brain Training" for older adults – does it work?"*

	Poster (2) "The impact of working memory training on theta power and reasoning in the group of elderly people"
December 2018	**Psych-On** (Łódź, PL) *Poster "Czy gry komputerowe poszerzają świadomość? Badanie z użyciem techniki ERP"* **(Awarded as the best poster of the conference)** *Speech "Wpływ treningu pamięci roboczej na moc w paśmie theta i rozumowanie w grupie osób starszych"* **(Awarded as the best speech of the session)**

Academic & Research Experience

Co-head of PlasticityTeam at Neurocognitive Research Centre, SWPS University	Main project: *Zmienność w czasie neuropoznawczych efektów treningu złożonym zadaniem w formie strategicznej gry komputerowej*" (ang. *Time variability of neurocognitive results of complex task in the form of a strategic video game*; project no: 2016/23/B/HS6/03843). Main responsibilities: developing the theoretical introduction and research questions, selecting the methodology, developing the qualification criteria for the study, creating experimental procedures, training the research team, coordinating the research and analysing the results.	**2019 - present**
Lecturer at SWPS University	My teaching experience includes conducting workshops and classes in the field of statistical analysis, EEG data analysis as well as work and calculations in a cloud environment. The classes I conduct focus on learning and using such languages as python, R, SQL, MATLAB.	**2020 - present**
Researcher at GamesLab, SWPS University	Main project: "*Rola psychofizjologicznych, poznawczych i motywacyjnych czynników w poprawie funkcji wykonawczych*" (ang. *The role of psychophysiological, cognitive and motivational factors in the improving executive functions*; project no: 2013/10/E/HS6/00186). Main responsibilities: data collecting and analysing of obtained results.	**2016 - 2019**

Teaching Achievements:	My elective workshop "Wprowadzenie do analizy danych EEG w MATLABie" (ang. *Introduction to EEG data analysis in MATLAB*) conducted in the winter semester 2021/2022 was rated by students above 4.8 on a 5-point scale.

Manuscripts comprising the thesis

Published articles:

Jakubowska, N., Dobrowolski, P., Rutkowska, N., Skorko, M., Myśliwiec, M., Michalak, J., Brzezicka, A. (2021) The role of individual differences in attentional blink phenomenon and real-time-strategy game proficiency. *Heliyon*, 7(4). DOI: 10.1016/j.heliyon.2021.e06724

IF: 3.776 **MNISW**: 40 **Contribution percentage:** 85

My contribution: data analysis (performing analyses, describing and presenting the results – tables, figures), reviewing the literature, writing the manuscript, preparing the manuscript for sending, formulating responses to reviews and preparing a revised version of the manuscript.

Jakubowska N., Dobrowolski, P., Binkowska, A.A., Arslan, I.V., Myśliwiec, M., Brzezicka, A. (2021) Psychophysiological, but Not Behavioral, Indicator of Working Memory Capacity Predicts Video Game Proficiency, *Frontiers in Human Neuroscience*, 15. DOI: 10.3389/fnhum.2021.763821

IF: 3.474 **MNISW**: 100 **Contribution percentage**: 87

My contribution: data analysis (performing analyses, describing and presenting the results – tables, figures), reviewing the literature, writing the manuscript, preparing the manuscript for sending, formulating responses to reviews and preparing a revised version of the manuscript.

Unpublished manuscripts (in review):

Jakubowska, N., Arslan, I.V., Chałatkiewicz, I., Dąbkowska, M., Podolecka, W., Brzezicka, A. Video game proficiency predicted by EEG oscillatory indexes of visual working memory. Article awaiting for reviews in *Frontiers in Psychology*.

IF: 4.232 **MNISW**: 70 **Contribution percentage** 87

My contribution: data analysis (performing analyses, describing and presenting the results – tables, figures), reviewing the literature, writing the manuscript, preparing the manuscript for sending

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Research article

The role of individual differences in attentional blink phenomenon and real-time-strategy game proficiency

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A R T I C L E I N F O

Keywords: Attentional blink Video games Real-time strategy Cognitive training Individual differences Event-related potentials (ERPs)

A B S T R A C T

The impact of action videogame playing on cognitive functioning is the subject of debate among scientists, with many studies showing superior performance of players relative to non-players on a number of cognitive tasks. Moreover, the exact role of individual differences in the observed effects is still largely unknown. In our Event-Related Potential (ERP) study we investigated whether training in a Real Time Strategy (RTS) video game StarCraft II can influence the ability to deploy visual attention measured by the Attentional Blink (AB) task. We also asked whether individual differences in a psychophysiological response in the AB task predict the effectiveness of the video game training. Forty-three participants (non-players) were recruited to the experiment. Participants were randomly assigned to either experimental (Variable environment) or active control (Fixed environment) group, which differed in the type of training received. Training consisted of 30 h of playing the StarCraft II game. Participants took part in two EEG sessions (pre- and post-training) during which they performed the AB task. Our results indicate that both groups improved their performance in the AB task in the post-training session. What is more, in the experimental group the strength of the amplitude of the P300 ERP component (which is related to a conscious visual perception) in the pre training session appeared to be predictive of the level of achievement in the game. In the case of the active control group in-game behaviour appeared to be predictive of a training-related improvement in the AB task. Our results suggest that differences in the neurophysiological response might be treated as a marker of future success in video game acquisition, especially in a more demanding game environment.

Introduction

Video games and cognitive functioning

Playing video games (VG) is undoubtedly one of the most popular leisure activities in today's society. However, besides being an engaging form of entertainment, playing video games has been also discussed recently in the context of its potential consequences on attentional and perceptual skills (e.g., Bavelier et al., 2011; Franceschini et al., 2013; Green and Bavelier, 2003; Toril et al., 2014). Particularly video games defined as “action video games” are thought to exert a significant influence on human cognitive functioning. According to Green and Bavelier (2003) video games that can be classified to this category need to: “have fast motion, require vigilant monitoring of the visual periphery, and often require simultaneous tracking of multiple targets”. In fact, the cumulative evidence suggests that expert action VG players outperform non-players in a number of cognitive tasks measuring such skills as visual attention, some aspects of cognitive control, general processing speed or working memory (e.g., Blacker and Curby, 2013; Castel et al., 2005; Colzato et al., 2013; Dye et al., 2009a, b; Green and Bavelier, 2003, 2006, 2007; Strobach et al., 2012). What is more, according to recent investigations, even relatively short training in action VG playing (e.g., 10 h) can improve subjects' performance in a subsequent cognitive examination (e.g., Basak et al., 2008; Feng et al., 2007; Li et al., 2010).

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Given that, in the light of recent meta-analyses (e.g., Dougherty et al., 2016; Guye and von Bastian, 2017; Melby-Lervåg et al., 2016; Sala and Gobet, 2019), traditional cognitive-training programs (e.g. . Jaeggi et al., 2010) bring little benefits and have minimal effect on domain-general cognitive skills, it comes as no surprise that VGs have started to be seen as a potentially promising new tool for enhancing cognitive skills. The resemblance of game-environment and its dynamics to real-world complexity as well as their inherently motivating character are currently considered as their greatest assets that could be profitable in the process of both restoring cognitive functions following brain impairments and in preventive cognitive interventions (Achtman et al., 2008).

The impact of VG playing on cognitive functioning has also become the subject of a heated debate among scientists, with some of them even undermining the relation between VG experience and cognitive abilities (Unsworth et al., 2015). Indeed, there is a plethora of studies showing also either none or weak impact of video-game playing on cognitive functions such as working memory or selective attention (e.g., Boot et al., 2008; Irons et al., 2011; Murphy and Spencer, 2009; Unsworth et al., 2015). Those discrepancies can, however, result from numerous methodological and statistical shortcomings, such as very small samples, extreme-groups designs, lack of standardized trainings, no active control groups and lack of independent replications (Bisoglio et al., 2014; Boot et al., 2011; Unsworth et al., 2015), which are present in the field. Aiming to overcome the limitations of previous study designs, a number of new approaches towards research on video games have emerged.

New trends in research on video games

First of all, it has been acknowledged that so-called "action video games", which in the light of numerous studies have been identified as the most beneficial for cognitive functioning, are, in fact, a loosely defined category. Indeed, as demonstrated by Dobrowolski et al. (2015), expertise in two games, both classified as action video games - namely real-time strategy (RTS) and first-person shooter (FPS), can have differential impact on cognitive functioning, with RTS players - in contrast to FPS players - showing greater performance in task measuring abilities such as visual attention and task-switching as relative to non-players (Dobrowolski et al., 2015). Those results suggest that VG play benefits might be a function of the type of actions performed within the game (Dobrowolski et al., 2015). Therefore, it seems that both, the gameplay mechanics and its demands on cognitive functions as well as individual's behaviour in the game environment, has to be taken into consideration during planning and analysis of studies in the field.

Furthermore, numerous investigations suggesting the positive impact of video games on cognitive functioning based their evidence on comparisons between expert video gamers and non-gamers. Those studies are therefore correlational in nature. It is likely that the mechanisms through which playing certain video-games influences cognitive functions are more complex, with multiple factors contributing to the observed differences. One of such factors might be a self-selection effect, as it is possible that future video game experts demonstrate superior perceptual, attentional, and cognitive skills from the very beginning of their gaming adventure and these initial predispositions promote video game expertise (Boot et al., 2008). In fact, as demonstrated by Kramer and Erickson's research group (Erickson et al., 2010), variability in performance in demanding video games can be predicted from variations in the pre-training volume of striatum. We found a similar pattern of results (Kowalczyk et al., 2020). These results seem to suggest that neuroanatomical differences can serve as effective predictors of procedural learning and cognitive flexibility during complex skill acquisition. What is more, similar effects have been also observed, for example, in the context of hippocampal volume and effectiveness of memory training (Engvig et al., 2012) and the value of such predictive models in the field of cognitive neuroscience has been already recognized as well (Gabrieli et al., 2015). This shows how important it is to employ a training design to investigate the impact of VG playing on cognition.

Present study

In our study we wanted to further investigate the mechanism through which playing video games might exert influence on cognitive functioning. Given that numerous studies emphasize not only the superior performance of action video game players as relative to non-players in attention-demanding tasks (e.g., Chisholm et al., 2010; Dye et al., 2009a, b; Hubert-Wallander et al., 2011), but also differences in neural strategies and mechanisms employed by those two populations during such tasks (e.g., Bavelier et al., 2012; Krishnan et al., 2013; Mishra et al., 2011), we decided to focus our research on changes in attentional skills. Aiming to precisely track the process of gaining those skills in the game environment, we designed a training procedure during which participants were learning to play a real-time strategy (RTS) game. To provide participants with both a cognitively-demanding and ecologically valid training environment, we chose RTS video game StarCraft II (SC2) – described as bearing close resemblance to "the messiness of the real world" (Vinyals, 2016) – for a training tool.

Furthermore, in order to assess post-training change in attentional skills and, at the same time, take into account individual differences in this domain, we measured participants' performance in the same cognitive task before and after the training. We chose Attentional blink (AB) task as a pre- and post-training measure for two main reasons: (i) AB paradigm has been widely investigated in the VG players population and, in the light of current research, is considered to be an adequate measure of temporal aspects of attentional processing (e.g., Green and Bavelier, 2003; Luck et al., 2000; Vul et al., 2008) (ii) its behavioural effects and neurophysiological underpinnings have been extensively studied and described in the existing literature (review: Martens and Wyble, 2010). Therefore, by examining the susceptibility of AB effects to the RTS video game training, we could not only test the influence of RTS training on attention but also contribute to the wealth of knowledge in this field.

Finally, while participants were completing both pre- and post-training measurements, their brain activity was recorded with the use of electroencephalography (EEG) technique, which served us as a benchmark for obtained behavioural results and allowed us to create individual profiles of subjects also on a neurophysiological level. Similarly to other studies (e.g., Koivisto and Revonsuo, 2008; Kranczioch et al., 2003; Mishra et al., 2011; Sergent et al., 2005), we applied an Event-Related-Potential (ERP) technique to analyze collected EEG data.

Attentional blink task

The attentional blink (AB) phenomenon is defined as a transitory impairment of attention appearing when multiple targets need to be processed in close temporal proximity. In laboratory settings this phenomenon is usually studied by task described as rapid serial visual presentation (RSVP). The Attentional Blink task, originally presented by Raymond et al. (1992), described the RSVP paradigm as consisting of a series of stimuli which are displayed at a single location with a frequency of about 10 per second. In the stream of stimuli two are defined as targets. The second target (T2) is presented at various time lags following the first target (T1). Within this framework, the AB phenomenon manifests itself as the inability of subjects to report on the second target (T2) when it is presented between 200-500 ms after the first one (T1) (Kranczioch et al., 2003).

Invariant and stable as it seemed at first, in the light of current investigations, the AB effect appears to be surprisingly susceptible to individual differences, with its magnitude varying from one individual to another (Martens et al., 2006). What is more, as revealed by recent studies, certain experiences can attenuate AB effect (review: Martens and Wyble, 2010). Frequent playing in action video games has been shown to be one of such experiences, with video game players outperforming non-video game players in detecting stimuli in the AB time window. The difference in performance between these two populations is thought to result either from faster target processing or increased ability to maintain several attentional windows in video-game players (Green and Bavelier, 2003; Oei and Patterson, 2013).

Despite numerous studies addressing factors influencing AB phenomenon, its neurophysiological underpinnings are still a matter of debate. Recent studies seem to suggest, however, that targets presented in the AB time window can reach working memory, which is reflected at the neurophysiological level in the modulation of the P300 ERP component (Kranczioch et al., 2003).

P300 is an ERP component with the peak latency varying from 250 to 650 ms after stimulus. It is thought to represent the activity of the widespread fronto-parietal networks and to be related to engagement of attentional resources and working memory processes, which are both crucial for dealing with cognitive tasks (Bonala and Jansen, 2012; Verleger et al., 2016). In the studies employing AB paradigm, the P300 component - in contrast to earlier ERP components such as P1 or N1 - has been shown to be evoked only by targets which were detected during blink interval (Kranczioch et al., 2003; Sergent et al., 2005; Sessa et al., 2007). As Kranczioch et al. (2003) suggested, such results can be interpreted as the evidence that relevant information presented during the AB time window is not entirely lost, but, one the contrary, in some trials, can be compared with templates held in working memory. In the light of those investigations, the P300 component might be thus considered as a marker indicating the depth of information processing. Furthermore, it can also act as a reliable neurophysiological measure of changes in cognitive functioning since its latency and amplitude have been shown to be sensitive to cognitive impairments, such as for example memory loss (Lai et al., 2010). To the best of our knowledge, however, its role in marking post-training changes in stimuli processing in the AB task has not yet been investigated.

StarCraft II

StarCraft II is a real-time strategy game, which is considered to be an excellent research platform for studying complex skills acquisition. A rich and dynamic task environment, accurate measures of motor performance, attentional allocation and perceptual processing, entertaining character, large datasets with numerous variables and many levels of expertise are listed as its main advantages (Thompson et al., 2013). The game itself is cognitively challenging, as it requires precise timing (taking action as soon as it is available), speed (issuing as many actions as possible) and spatial precision (targeting the right place, structure or unit). What is more, according to studies in the field, extensive and long-term RTS experience can induce neuroplastic changes. Particularly, RTS players appear to have significantly more total white matter connections between occipital and parietal areas and within occipital areas as compared to non-players (Kowalczyk et al., 2018). Accordingly, behavioural studies indicate enhanced visual and spatial skills in RTS players (Dobrowolski et al., 2015; Kim et al., 2015). The expertise in the game is also associated with an increase in the number of attentional shifts that occur within a set time frame (Thompson et al., 2013) and training in SC2 has been reported to have a positive effect on cognitive functioning (Glass et al., 2013). Importantly, StarCraft II allows for creating various game environments differing in the amount of cognitive effort the playing requires. This way, similarly to the video-game training employed in the study of Erickson et al. (2010), it is possible to create two groups – experimental promoting cognitive flexibility by encouraging the use of numerous different strategies (in our study called: Variable) and the active control in which optimal strategy is not to prioritize different aspects of task flexibly, but rather to use “flat” priority approach (in our study called: Fixed).

Research goals

Our study employed two versions of StarCraft II video game as cognitive training in order to determine if we can observe different outcomes depending on the level of game complexity (Variable versus Fixed). We posed two kinds of research questions to frame our current study. Firstly we were interested how our participants will change after training at the behavioural level. Would we be able to observe a bigger improvement in the post-training relative to the pre-training performance in the AB task (i.e. higher accuracy in detecting T2 in the AB time window) in the experimental (Variable) group compared to the active control (Fixed)? Secondly, we wanted to look at the variables on the electrophysiological level and see if we can observe the P300 ERP component in response to the detected targets presented in the AB time window (T2) and, if so, whether a post-training improvement in the AB task would be reflected on the neurophysiological level (i.e. difference between sessions and difference between groups in the mean amplitude of the P300 ERP).

We were also interested in the predictive power of our behavioural and psychophysiological variables. Would we be able to predict the performance of players in the game based on initial variability in cognitive indicators (i.e. the accuracy in the AB task in the pre-training examination)? Can we predict the performance of players in the game based on initial psychophysiological indicators (i.e. the magnitude of P300 component amplitude in the pre-training session)? And, what is most important, which of these predictors will be stronger in regards to training's effectiveness. We have also asked a question about in-game behaviour (which we treat as a proxy for the training's impact) as a predictor of a post training cognitive gain (measured as a difference between pre- and post-training performance in the AB task).

Methods

Participants

A total of 70 participants were initially recruited online via a covert questionnaire (Sobczyk et al., 2015). As a result of (1) resignation (n = 8), (2) wrong hardware configuration (n = 7), (3) failure to meet all training objectives (n = 4), (4) bad quality of data (n = 7) or (5) lost data (n = 1) only 43 of participants were included in analyses reported here. Participants were randomly assigned to two training groups: experimental - Variable (n = 21; 13 males; M_{age} = 24.71, SD = 3.15) and active control - Fixed (n = 22; 10 males; M_{age} = 25.13, SD = 2.96). The participants reported normal or corrected-to-normal visual acuity, normal color vision, and normal hearing. They were right-handed and reported not being on any medications, no history of neurological or psychiatric disorders and injuries, including no previous head trauma, no previous head or neck surgery and no brain tumors. All participants declared less than 5 h of video games played per week over the past six months and no experience with Real Time Strategy or First Person Shooter games. Informed consent was obtained from each participant before the start of the experimental procedure. Initially, we had 34 participants additionally assigned to a passive control (PC) group (n = 16, 8 males; M_{age} = 24.69, SD = 2.87) or additional active control (AAC) group (n = 18, 10 males, M_{age} = 25.11, SD = 3.88). As a result of (1) resignation (PC: n = 1; AAC: n = 4), (2) failure to meet all training objectives (AAC: n = 2) (3) bad quality of data (PC: n = 2; AAC: n = 2), and (4) lost data (PC: n = 4; AAC: n = 1) we excluded passive control and additional active control groups from analyses and focused on comparisons of our two RTS training groups [experimental (Variable) and active control (Fixed)]. Then it is important to mention that dropout is a common problem in longitudinal, training studies (e.g. Moore et al., 2017). Furthermore, our study employed restrictive recruitment criteria, which finally resulted in an inability to re-complete the control groups.

Procedure

Ethics Committee of the SWPS University of Social Sciences and Humanities approved the study design and the informed consent form. The research consisted of three steps: (1) Pre-training measurement of cognitive function via Attentional Blink task, (2) Training sessions, and

(3) Post-training measurement (Figure 1). Experimenters were present in all meetings. Measurement and training sessions took place in the laboratories of the SWPS University in Warsaw.

Experimental procedure

Prior to the beginning of the experiment, participants were verbally instructed as to what they would be experiencing and were shown what the procedure of EEG electrode mounting entails. Then, after signing a consent form, participants were brought into a laboratory setting and seated in front of a 24 inch BenQ XL2411Z computer monitor (1920 1080 resolution, 100Hz refresh rate) at a distance of 60 cm. Electrodes were then mounted and participants were briefly shown the EEG signal and explained how it is affected by eye blinks and muscular movements, which was a part of the procedure aimed at minimizing the amount of artifacts in the signal. The procedure was then started, and upon its completion subjects were provided with a place to wash their hair. The entire procedure lasted no more than 2 h and was identical during both measurements. All subjects, who fulfill training requirements and participated in both measurement sessions, were compensated for their participation with approx. 184 USD after post-training measurement.

Experimental task – attentional blink paradigm

The experimental task was based on the procedure outlined by Kranczioch et al. (2003). In each trial, a stream of either 16 or 19 letters (1.0–1.8 deg. x 1.3 deg.) appeared in a sequence on a white background. Participants were asked to detect two types of targets in the stream of letters: T1 and T2 (see Figure 1b). T1 appeared as a green capital letter that could be either a vowel (all except for I) or a consonant (all except for F, K, Q, X, Z). T2 was always a black capital letter X. The remaining non-targets were randomly chosen black consonants (except F, K, Q, X, Z), with the restriction that two adjacent letters in a stream could not be identical. In the case of 16 letter trials T1 would always appear as the fourth letter, and for 19 letter trials it would appear as the seventh. T2 could appear at a "lag" of one, two, or seven items after T1. At the end of each stream participants were asked to indicate: (1) if a vowel was present in the letter stream and (2) if the letter X appeared in the stream. Responses were given as "yes" or "no". Stream length, T1 type (vowel or consonant), and T2 lag were evenly split across 16 practice trials and four blocks of 64 trials, within randomization of trial order within each block. No T2 appeared in 25% of the trials. As the presented paradigm represents the most classic AB task model, it allows us to compare our findings with the results obtained by previous research.

Training

StarCraft II training

The StarCraft II (SC2) training consisted of 30 h of training time over a four-week period. Training consisted of playing matches (approx. 20 minutes each) against SC2's artificial intelligence (AI), and all matches were played at our laboratory. Participants were required to train a

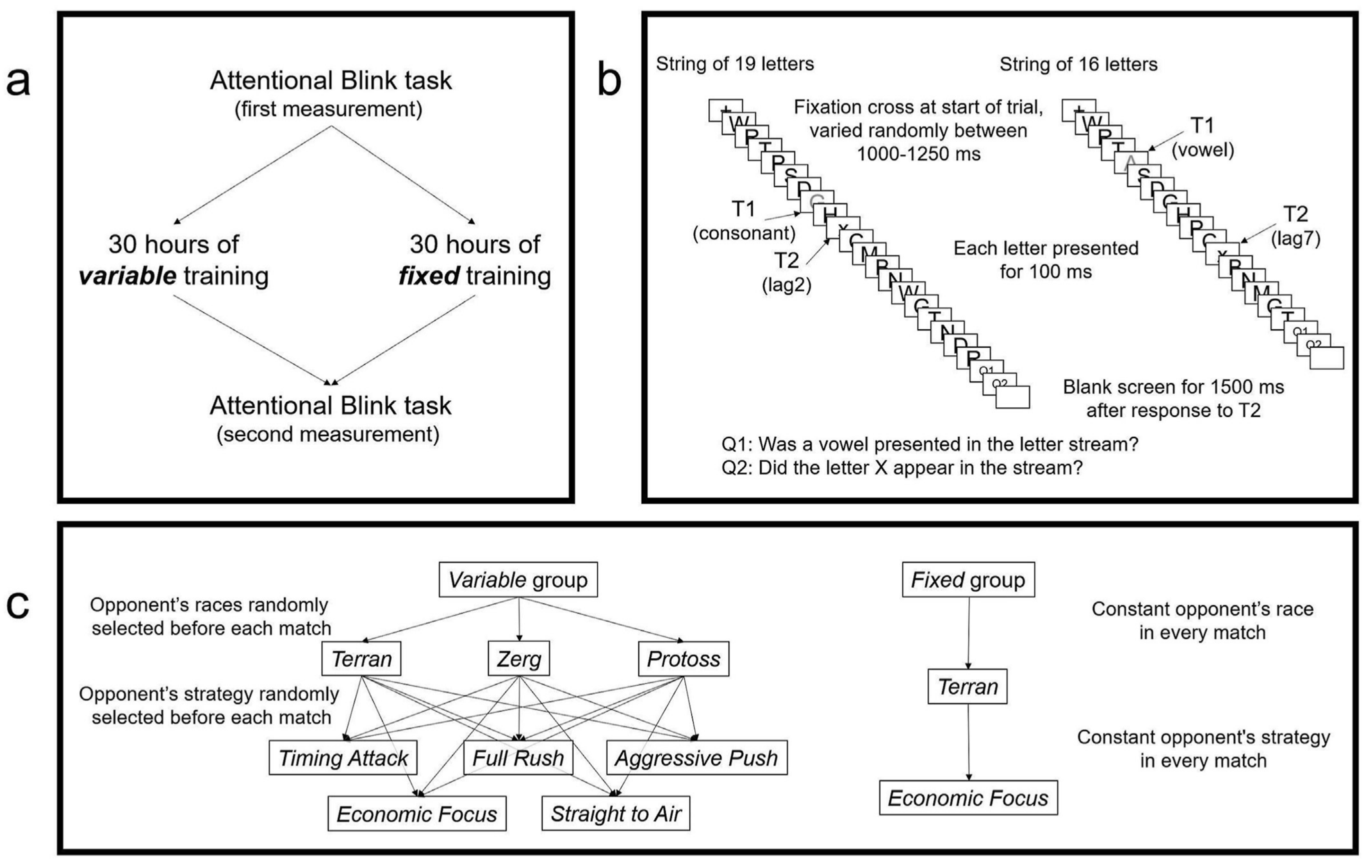

Figure 1. (a) Study design: two measurement sessions were carried out during the study (pre-training and post-training). Training included 30 h of playing in the real-time strategy game (*StarCraft II*), spread over 4 weeks. Training varied depending on the group. (b) Example of two trials of Attentional blink task. The first trial consists of 19 letters. T1 is presented as a green letter G, and the "X" (T2) appears in Lag 2. The second trial consists of 16 letters, where T1 is presented as a green A letter, and "X" (T2) appears in Lag 7. Each trial started with a fixation cross after which a string of (16 or 19) letters was presented. Each letter was presented for 100 ms and then participants were asked about the type of T1 and the presence of T2. Each trial ended with a blank screen presented for 1500 ms after response to the second question. (c) While all of the participants played as a Terran faction during training, the opponent's race and strategy varied according to the training group type. Participants from the Variable group could match three factions, from each could use one of five strategies. The faction and the strategy were randomly selected before each match for the Variable group. In the case of a Fixed group, participants always played against the Terran faction, which used an economic strategy.

minimum of 10 h per week, but no more than 5 h per day. This was done to avoid excessive skew in the distribution of training hours across the training period. There were also two possible training types: Fixed and Variable. The exact differences between the types of the training are described below and were presented in Figure 1.

Participants had to access an online platform before each match in order to receive configuration parameters; the parameters consisted of the difficulty setting, the opponent's faction, the opponent's strategy, and the game map. Participants from both groups played all of their matches as a Terran faction. While the map was randomly selected from 14 maps before each match in both - Fixed and Variable - training versions, the opponent's faction and strategy only varied in the Variable group. The Fixed group always faced the same faction (Terran), and their opponent always applied a more passive "Economic Focus" strategy. The Variable group could face any of the three factions (each with their own unique units and abilities) and also any of five opponent strategies: Full Rush, Timing Attack, Aggressive Push, Economic Focus, Straight to Air. Game difficulty was set adaptively for both training types spanning across seven levels. The online platform software recorded the number of wins (þ1) and losses (-1) and each time the total passed the multiple of 4 threshold, the difficulty was increased by one. The difficulty decreased whenever the total dropped below the multiple of 4 threshold. The training was preceded by an introduction phase designed to familiarize participants with the core concepts of the game and basic gameplay mechanics (see next section).

StarCraft II introduction

The introductory phase consisted of eight parts: (1) a short text describing the goals of the meeting; (2) a text and video based description of the overall game; (3) a video introduction to the Terran faction, its units and buildings; (4) a text based description of the fundamental game concepts and in-game interface; (5) an AI guided tutorial that introduces the gameplay in real time, allowing participants experience the game for the first time; (6) a quiz requiring that the correct labels be attached to each of the five basic unit and building types that are available to the Terran faction, which was intended to check if participants were attentive to the training materials; (7) two films (25 min each) describing basic strategies and explaining the various stages that each match progresses through; and (8) a three-match series in which the game progressively increased its difficulty, speed and available units, with no specific guiding instructions. The entire introduction lasted approx. 2.5 h, and did not count into the required 30 h of training. It was also automated and self-paced, with experimenters only providing assistance when needed and also during part 8 of the introduction where assistance was provided to keep up the pace and direction of each training game. Upon completion of this introduction, participants were free to begin training on the following day.

Data reduction and analysis

All analyses were conducted using IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp., R Statistical Software (Foundation for Statistical Computing, Vienna, Austria) and MATLAB custom scripts.

Telemetric data

Independently of the group, training created in the study resulted in 8 levels of matches' difficulty: (1) Very Easy, (2) Easy, (3) Medium, (4) Hard, (5) Harder, (6) Very Hard, (7) Elite and (8) Cheater. The level of difficulty corresponded to the win ratio of previously played matches, which enabled steady progress in the game environment. Due to the fact that only four of participants could reach the top two levels, Elite and Cheater levels were excluded from further analyses. Maintain levels were later divided into three categories: the easiest levels (Very Easy level, Easy level), the middle levels (Medium level, Hard level) and the hardest levels (Harder level, Very Hard level). The game performance of two experimental groups was compared through a series of *t* tests.

Behavioural data

Accuracy rates for each lag were calculated. To reveal attentional blink effect, detection rates at specific lags were compared with *t* tests for dependent measures. To calculate Lag, Session and Group effects, 4 2 2 ANOVA for repeated measures was created.

EEG data

A 64-channel SynAmps RT Neuroscan EEG amplifier and BrainProducts actiCap Ag/AG-Cl active electrode set were used to record brain activity during task performance. All channels were recorded at 1000 Hz sampling rate. Impedances were held below 5 kΩ. All data were preprocessed offline using MATLAB environment and EEGlab (Delorme and Makeig, 2004), and ERPlab (Lopez-Calderon and Luck, 2014) software packages. The signal was initially re-referenced to a common average and then down-sampled to 250 Hz, followed by a band-pass filter between 0.1 and 40 Hz. Data epochs between -0.2 and 0.996 s (with zero being the T2 presentation) were extracted, and all epochs with incorrect behavioral responses were rejected. The remaining epochs were manually filtered for eye-blinks/movements and excessive muscle activity, and then averaged.

The P300 component mean amplitudes were extracted from 375-625 ms time window after T2 presentation, which is a standard window for P300 from AB task (see literature: Barry et al., 2020; Dell'acqua et al., 2003; Kranczioch et al., 2003) and activity observed on the corre- sponding topographical maps of the scalp. It was analyzed with a 3 (Lag: lag 1 vs lag 2 vs lag 7) x 2 (Sessions: pre-training vs post-training) x 2 (Group: Fixed vs Variable) repeated-measures ANOVA, with Lag and Sessions as the within-subjects factor and Group as the between subjects factor.

Moderation analyses

Multiple moderation models were estimated through the PROCESS macro (Hayes, 2018) for SPSS Statistics. All of the used variables were standardized to avoid multicollinearity and to make interpretations more straightforward.

Results

Game performance

We started by calculating the average time spent in the game and the mean number of played matches. Although there were no significant difference between groups in time spent playing SC2 ($p = 0.816$), participants from Variable group were able to played more matches in that time period (Variable group: Mean = 100.19, SD = 23.997; Fixed group: Mean = 82.545, SD = 12.078); $t(29) = 3.024$, $p = .005$ (Figure 2c and Figure 2b). It is a result of the fact that participants from Variable group played more matches on Harder level (Variable group: Mean = 22.762, SD = 19.621; Fixed group: Mean = 8.545, SD = 16.387); $t(39) = 2.573$ $p = .014$ and on Very Hard level (Variable group: Mean = 11.143, SD = 13.016; Fixed group: Mean = 3.727, SD = 10.152); $t(37) = 2.077$, $p = .045$. On the other side, participants from Fixed group played more matches on Medium level [Variable group = 20.857, SD = 13.074; Fixed group = 29.773, SD = 17.498); $t(38) = -1.898$, $p = .065$] what is shown in Figure 2a.

Behavioral results

Previous investigations have shown that subjects often fail to report T2 when it is presented within 200–500 ms after T1, whereas when the interval is longer, both targets are usually reported correctly (Chun and Potter, 1995; Raymond et al., 1992; Ward et al., 1997). Importantly, when T1 and T2 are presented about 100 ms apart, subjects quite often

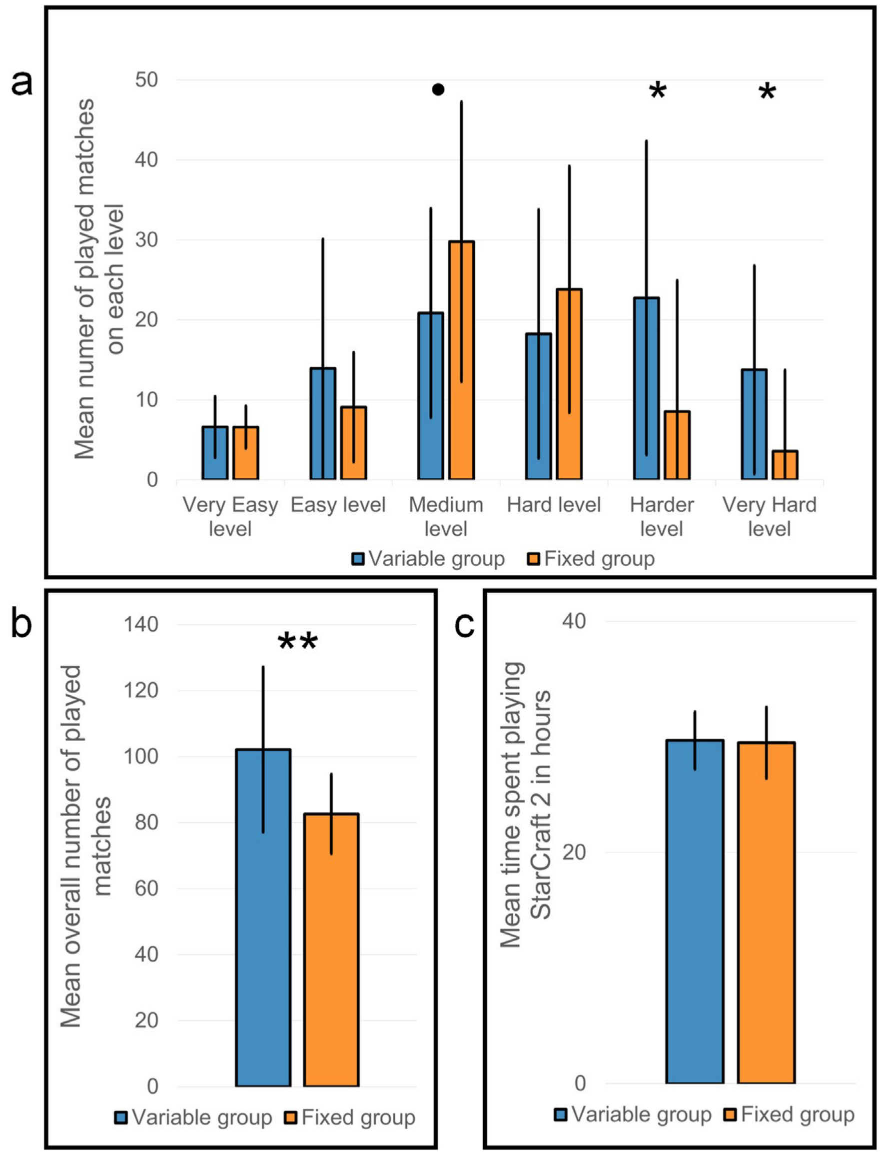

Figure 2. (a) Mean number of matches played on each level during training for Variable and Fixed groups. (b) Mean overall number of matches played during training for Variable and Fixed groups. (c) Mean overall time spent in training for Variable and Fixed groups. Asterisks indicate statistical significance: p = .07, * p < .05, ** p < .01, *** p < .001.

report both targets. So, we started our analysis from checking whether these two basic trends occurred in our study (Figure 3).

An attentional blink effect was detected with mean T2 detection rates from both sessions at Lag 2 being lower than at Lag 1, t(83) = -3.746, p < .001, 95% CI of Lag 2/Lag 1 difference [24.198, -7.415], and at Lag 7, t(83) = -5.955, p < .001, 95% CI of Lag 2/Lag 7 difference [31.119, -15.438], which stands in agreement with the literature (e.g. Constable et al., 2018; Kranczioch et al., 2003). Due to the fact that attentional blink effect was confirmed, behavioral data were analyzed using a 4 (Lag: lag 1 vs lag 2 vs lag 7 vs No T2) x 2 (Sessions: pre-training vs post-training) x 2 (Group: Fixed vs Variable) repeated-measures ANOVA, with Lag and Session as the within-subjects factors, Group as the between subjects factor and accuracy as a dependent variable. It revealed main effects of Lag [F(3,39) = 34.316, p < .001, η^2 = .474] and Session [F(1,41) = 11.217, p = .002, η^2 = .215) as well as a Lag Session interaction [F(3, 39) = 5.744, p = .002, η^2 = .306] what is depicted in Figure 3a. No interaction effect with the Group was found (Lag x Group: F(3, 39) = 1, 027, p = .391, η^2 = .073; Session x Group: F(1, 41) = 1.583, p = .215; η^2 = .037; Lag x Session x Group: F(3, 39) = .652, p = .586, η^2 = .048] and we observed a similar pattern of improvement after training in both groups (Figure 3). .

Psychophysiological results

As P300 component is associated with conscious processing of stim- uli, previous investigations have shown not only that P300 component evokes as a result of item detection, but also may be significantly more positive in some Lag conditions in the AB task. We wanted to investigate if the positivity of P300 - as a reaction to the visual stimuli - will increase after complex cognitive training, which should affect a number of cognitive skills involved in stimulus detection. ANOVA analyses revealed that there were neither main effects of Lag [F(2, 40) = .720, *p* = .488, η^2 = .003, Session [F(1, 41) = .906, *p* = .342, η^2 = .002], interaction be- tween them [F(2, 40) = .574, p = .565, η^2 = .002], Lag Group- interaction [F(2, 40) = .270, p = .764, η^2 = .001] or Lag x Session Group interaction [F(2, 40) = .800, p = .45, η^2 = .003]. Still, variable group increased their P300 amplitude power in the post-training mea- surement, while Fixed group's P300 decreased, which resulted in

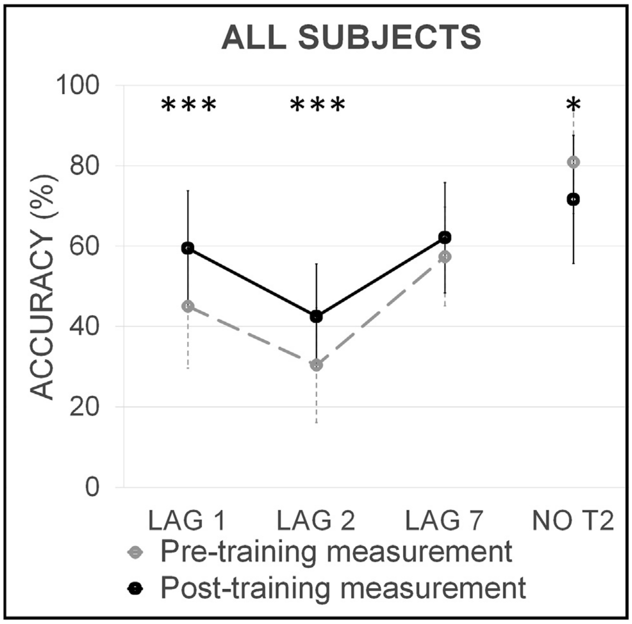

Figure 3. (a) Comparison of accuracy from attentional blink task between sessions at every Lag condition and in No T2 appearance condition for each training group. We observed very similar changes for lag conditions in both groups but all effects were stronger in a Variable group (b) than in Fixed group (c). Asterisks indicate statistical significance ($p = .09$, * $p < .05$, ** $p < .01$, *** $p < .001$).

significant Session Group interaction [$F(2, 40) = 5.722$, $p = .018$, $\eta^2 = .012$] and which is visible in Figure 4a and b.

Moderation analyses

The mean P300 amplitude from the pre-training measurement as a predictor of the number of matches played on the hardest levels

In order to better understand the observed differences in game performance between our training groups, we started looking for behavioral or neurophysiological predictors of game performance. In order to test the predictive value of the initial neurophysiological index of attention in each of our training groups we performed a series of analysis with indicators describing how well our participants dealt with the game's requirements serving as dependent variables. Separate moderation analyses were performed to clarify whether initial mean P300 amplitude predicted the number of matches played on each difficulty level and whether this relationship was moderated by the training type. As there were no differences between Lag conditions in the mean P300 component, we used mean P300 amplitude which were averaged across all lags.

We created a model containing mean amplitude of a P300 component from the pre-training measurement as a predictor, Group as a moderator variable and mean number of matches played on the hardest levels (Harder and Very hard combined) as a dependent variable (Figure 5a). Created model turned out to be significant [$F(3, 39) = 4.617$, $p = .007$, $R^2 = .262$] and contained significant influence of the Group [$b = -.352$, $t(39) = -2.546$, $p = .015$] and interaction between mean P300 component from pre-training measurement and Group [$b = -.3704$, $t(39) = -2.508$, $p = .016$]. Next, it was revealed that while for the Fixed group there was no relationship between initial P300 component amplitude and number of matches played on the hardest levels ($p = .318$), for the Variable environment group we saw a significant positive relationship: the stronger initial P300 amplitude the more matches one played on the hardest levels of the game (one unit increase in the average P300 component's amplitude from pre-training measurement resulted in an increase of .56 in a number in matches played on that levels [$t(39) = 2.359$, $p = .023$]).

Then two subsidiary models were created for both: Harder and Very Hard levels (Figure 5b). Both models turned to be significant [Harder level: $F(3, 39) = 3.94$, $p = .015$, $R^2 = .232$; Very Hard level:. $F(3, 39) = 4.33$, $p = .01$, $R^2 = .25$] and both presented same tendencies: (1) influence of the Group [Harder: $b = -.354$, $t(39) = -2.512$, $p = .016$; Very Hard: $b = -.296$, $t(39) = -2.124$, $p = .04$] (2) interaction between P300 component recorded during pre-training measurement and Group [Harder level: $b = -.304$ $t(39) = -2.018$, $p = .05$; Very Hard level: $b = -.42$, $t(39) = -2.826$, $p = .007$], (3) through for the Fixed group both relationship turned to be truly insignificant (Harder level: $p = .599$; Very Hard level: $p = .118$), there was positive relationship between P300 component and number of matches played on each level for the Variable group [Harder Level: $b = .509$, $t(39) = 2.101$, $p = .042$; Very Hard level: $b = .559$, $t(39) = 2.331$, $p = .025$].

Further analyses did not show a similar relationship for other levels, which were available in the game. All subsequent analyses, attempting to predict the number of matches played on a given level, turned out to be insignificant.

Number of matches played on the easiest levels as a predictor of attentional blink task's improvement

Due to the fact that the game environment was varied and cognitively challenging through the training, games on specific levels should differently influence cognitive abilities of the subjects. Although participants from both groups spent on average the same number of hours playing SC2, their post training performance varied significantly. In order to elucidate the variation seen in behavioural results, we decided to include indicators from the game (number of matches played on a given level) environment in our analysis. As easy levels were the least cognitively demanding, we assumed that time spent on the easiest levels may adversely affect potential progress in the task and time spent on the harder levels may promote it.

We created a model with the number of matches played on the easiest levels as a predictor, Group as a moderator variable and difference in AB's task accuracy before and after training as a dependent variable (Figure 6a). Created model turned to be significant [$F(3, 39) = 3.38$, $p = .028$, $R^2 = .206$] and contained significant influence of the mean number of matches played on the easiest levels [$b = -.4$, $t(39) = -2.09$, $p = .043$] and interaction between number of matches played on the easiest levels and Group [$b = -.549$, $t(39) = -2.87$, $p = .007$]. Next, it was revealed that for the Variable environment group there were no relationship between predictor and training-related changes in the behavioral task ($p = .34$), but for the Fixed environment group we saw a negative relationship - the more matches played on the easiest level the weaker the improvement [$b = -.93$, $t(39) = -2.717$, $p = .009$].

Then again, two subsidiary models were created for both: Very Easy and Easy levels (Figure 6b). Both models turned to be significant [Very Easy level: $F(3, 39) = 2.852$, $p = .049$, $R^2 = .179$; Easy level: $F(3, 39) = 2.885$, $p = .047$, $R^2 = .182$] and both presented tendencies, which were revealed in the model described above: (1) there were interactions be- tween number of matches played on each levels and Group [Very Easy level: $b = -.387$, $t(39) = -2.498$, $p = .017$; Easy level: $b = -.535$, $t(39) = -2.62$, $p = .012$], and (2) through for the Variable group both relationship turned out to be truly insignificant (Very Easy level: $p = .402$; Easy Level: $p = .358$), there was a negative relationship between number of matches played on each level and difference in the accuracy from behavioral task for the Fixed group [Very Easy Level: $b = -.615$, $t(39) = -2.464$, $p = .018$; Easy level: $b = -.909$, $t(39) = -2.453$, $p = .019$].

Further analyses did not show a similar relationship for other levels available in the game. All subsequent analyses, attempting to predict difference in task accuracy, turned out to be insignificant.

Discussion

The initial aim of this study was to test the possibility of improving attention with an RTS video game. Our data show that playing RTS video-

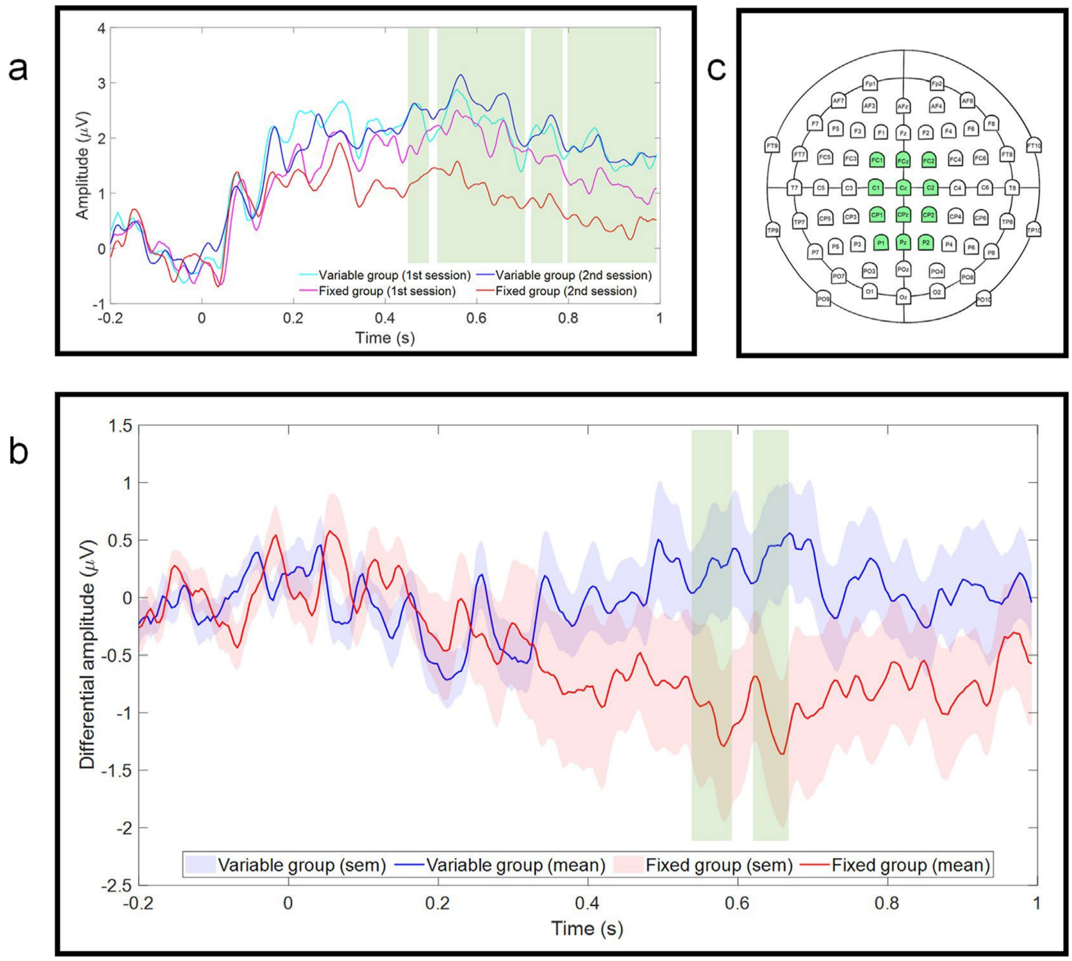

Figure 4. (a) Averaged brain activity recorded on the Cz electrode during attentional blink task, with 0 point being T2 presentation moment. Waves represent each group and measurement session separately, and waves were averaged over all lags. The green color specifies time when significant differences between Variable and Fixed groups were observed (in the 2nd session, so it was a difference between dark blue line and dark red which yield the significant effect). (b) Differential waves (2nd session minus 1st session) for each training group, with 0 point being T2 presentation moment. We can clearly observe opposite effects in amplitude change after training. (c) Localization of electrodes with indication from which electrodes we took signal for our analyses. Note that in graph 4a we are showing signals from a single electrode (Cz).

game can indeed enhance attentional skills, independently of the variant of game being trained. Our results, however, differ from the results obtained e.g. in studies comparing gamers and non-gamers, where expert gamers showed attenuated attentional blink relative to non-experts (see e.g. Wong and Chang, 2018). We did not observe change in the shape of attentional blink, we have rather seen an overall, non specific improvement in task performance. And, what is more important in the light of our hypotheses, this improvement was not dependent on the training type. We did, however, observe training specific effects on the physiological level, the P300 amplitude showed opposite changes in amplitude in fixed and variable training groups. What was even more interesting, the strength of the initial (pre-training) P300 component's mean amplitude appeared to be predictive of the in-game performance for the group playing a more demanding variant of the game (Variable group).

So we can ask: does a specific brain training protocol change every one's brain? Or does the training efficiency depend on an individual's brain? Our analysis indicates that the stronger the initial P300 amplitude the better was the progress of subjects in the game as measured by the number of matches played at most difficult levels. Importantly, this effect was visible only in participants subjected to a varied training regimen. As the P300 ERP component is usually related to such cognitive processes as focusing attention or conscious processing and acting (Bonala and Jansen, 2012; Verleger et al., 2016), its mean amplitude could correspond to participant's individual cognitive resource in that field. Since RTS games also place heavy emphasis on both - quick and well-suited - conscious reacting, it seems likely that this type of action video games is applicable for attention skills training. Then, our results imply that even players with existing predispositions can strengthen them by suitable stimulus (e.g proper training model) in order to develop and maximize their results. However, the pre-session behavioural accuracy, contrary to psychophysiological indicators, seems not to be predictive of player's game achievement. It might indicate that neurophysiological reactions are more sensitive and accurate in pinpointing individual differences in cognitive capacities and therefore be related to the broader spectrum of tasks (Ritter and Gaillard, 2000), than behavioural results.

Furthermore, the behaviour in the game environment appeared to be predictive of improvement in the AB task in the fixed game group. Specifically, participants who played more matches on the easiest levels of the game (which means they struggled to get higher and did not have a chance to practice more demanding actions) had worse improvement or even decrease of correctness in the AB task as measured by the difference between post- and pre-training sessions. A recent meta-analysis by Pallavicini et al. (2018) provides evidence that various video-games can have a different impact on many aspects of behaviour (see also: Oei and Patterson, 2015). Although we subjected both groups to the training of the same RTS video-game, the training modes were different (Variable

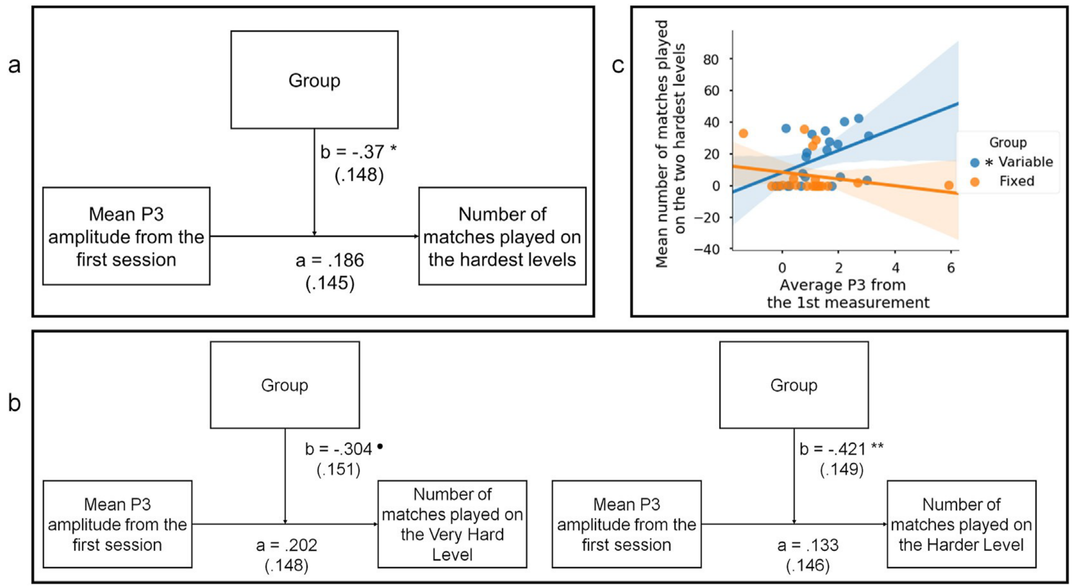

Figure 5. (a) The theoretical moderation model with the P300 component's mean amplitude obtained during pre-training measurement as a predictor, Group as a moderator variable, and the mean number of matches played on the two most difficult levels (which were included in the analyses) as an independent variable. (b) The theoretical moderation models corresponding to the specific levels, which were included in the model presented above. a and b are the path and interaction coefficients (unstandardized regression weights with standard errors in parentheses). Asterisks indicate significant regression paths ($p < .07$, * $p < .05$, ** $p < .01$, *** $p < .001$). (c) Relationship between P300 component's mean amplitude recorded during pre-training measurement and the mean number of matches played on each of the two most difficult levels. * symbol placed on the legend, corresponds to a significant effect (Variable group: Pearson's coefficient = .445, p = .043; Fixed group: Pearson's coefficient = -.242, p = .278).

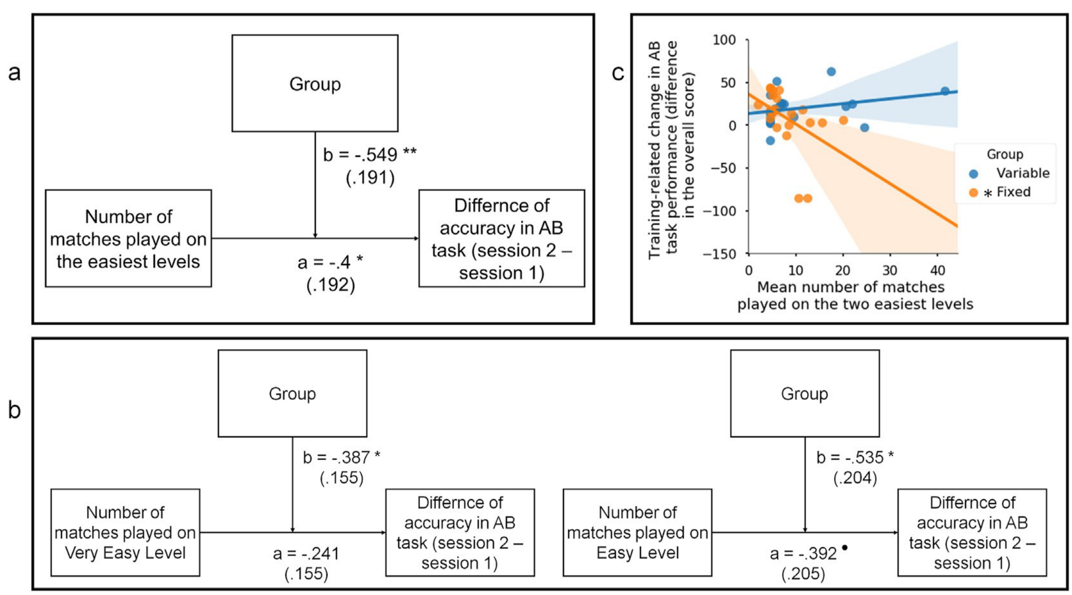

Figure 6. (a) The theoretical moderation model with the mean number of matches played on the two easiest levels as a predictor, Group as a moderation variable, and difference of accuracy in attentional blink task (session 2 accuracy rate – session 1 accuracy rate) as an independent variable. (b) The theoretical moderation models corresponding to the specific levels, which were included in the model presented above. a and b are the path and interaction coefficients (unstandardized regression weights with standard errors in parentheses). Asterisks indicate significant regression paths ($p < .07$, * $p < .05$, ** $p < .01$, *** $p < .001$). (c) Relationship between the number of marches played on the two easiest levels and task accuracy difference. * symbols placed on the legends correspond to significant conditions. Two versions of correlations were conducted: with the outlier presented on the graph (Fixed group: Pearson's coefficient = -.445, p = .038; Variable group: Pearson's coefficient = .304, p = .181) and without the outlier (Fixed group: Pearson's coefficient = -.445, p = .038; Variable group: Pearson's coefficient = .174, p = .464).

versus Fixed game environment) depending on the group. While in the Variable group participants had to learn more factions, units and master more strategies to properly develop in the game environment, Fixed group training process was predetermined and not able to be changed, and was depending more on repetition than skills developing. Then, it is understandable that the strength of training's influence was different between the groups. It is also important to realize that the relationship between the player's cognitive abilities and his performance in the game is bilateral. Progress in the game environment should match the level of the player's cognitive abilities, and then if a participant was not able to achieve higher levels of difficulty in the game, he also shouldn't be able to improve his result in the behavioural task.

It is interesting finding that participants subjected to a Variable training model, compared to the Fixed group, played more matches on the most difficult levels. Due to the wide diversity of opponents and their strategies, participants had to develop various strategies and master the most of game rules, which made their task more demanding. This may be partly due to being capable of maintaining their interest and involvement in the training process, which results in maintaining higher motivation. As each opponent required a different approach to the game, it is also possible that a Fixed training scenario, which did not enforce a player's certain behaviours, did not create adequate opportunities for the development of certain skills.

Overall our results suggest that the influence of RTS video-games largely depends on the training model. While the aspects by which games could affect specific cognitive skills, or how long it takes to induce such effect, are widely discussed (e.g. Bediou et al., 2018), previous investigations in that field rarely pay attention to usually limited gameplay and different training modes. Moreover, both - the impact of the game and the game achievements - may depend on the player's individual predispositions.

Considering the fast-growing e-sport industry, the topic of individual predispositions to being a good gamer seems to be exceedingly actual. While in the classic sports methods of measuring player predisposition or development seem to be well validated, in the e-sport such tools and methods are still under-investigated. As game playing is based on a number of cognitive functions, it may be necessary to build a wide range of carefully selected behavioural tasks, and to find their neurophysiological indicators, which may be more sensitive for small changes resulting during training. Then, video games should not be considered solely in terms of their popularity, the possibility of their application as a cognitive training tool in neurorehabilitation, or in terms of how they affect us, but also in terms of player's predispositions to achieve higher scores and methods of inspecting the training process.

In addition, it's important to mention that recent studies are still arguing about the importance of consciously perceiving stimulus in the process of encoding into the working memory (Jones et al., 2020). Then, future investigations should include a wider range of carefully selected tasks and analyses beyond the Attentional Blink paradigm used here. To be able to confirm the importance of the P300 ERP component as a predictor of specific cognitive skills acquisition, study should also include a group of RTS game's experts, whose electrophysiological and behavioural results could be compared to non-player's. Lack of group training another type of video game might be seen as a limitation of this study. Similarly, the fact that we did not compare our results to the control group makes our conclusions limited to the specific type of people.

Declarations

Author contribution statement

Natalia Jakubowska: Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.
Paweł Dobrowolski, Maciej Skorko: Conceived and designed the experiments; Performed the experiments.
Natalia Rutkowska: Contributed reagents, materials, analysis tools or data; Wrote the paper.
Monika Mysliwiec, Jakub Michalak: Performed the experiments.
Aneta Brzezicka: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

Data will be made available on request.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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Tytuł pracy: Jakubowska N., Dobrowolski P., Rutkowska N., Skorko M., Myśliwiec M., Michalak J., Brzezicka A. (2021) The role of individual differences in attentional blink phenomenon and real-time strategy game. *Heliyon*, 7. doi: 10.1016/j.heliyon.2021.e06724

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Psychophysiological, but Not Behavioral, Indicator of Working Memory Capacity Predicts Video Game Proficiency

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ORIGINAL RESEARCH
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Psychophysiological, but Not Behavioral, Indicator of Working Memory Capacity Predicts Video Game Proficiency

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Visual working memory (VWM) is the ability to actively maintain visual information over short periods of time and is strongly related to global fluid intelligence and overall cognitive ability. In our study, we used two indices of visual working memory capacity: the behavioral estimate of capacity (K) and contralateral delay activity (CDA) in order to check whether training in a Real-Time Strategy (RTS) video game StarCraft II can influence the VWM capacity measured by the change detection task. We also asked a question whether individual differences in behavioral and psychophysiological indices of VWM can predict the effectiveness of video game training. Sixty-two participants (non-players) were recruited to the experiment. Participants were randomly assigned to either experimental (Variable environment), active control (Fixed environment), and passive control groups. Experimental and active control groups differed in the type of training received. Training consisted of 30 h of playing the StarCraft II game. Participants took part in two EEG sessions (pre- and post-training) during which they performed the VWM task. Our results showed that working memory capacity (K calculated according to Pashler's formula) increases after training in both experimental groups, but not in a control group. We have also found a correlation between average visual working memory capacity (calculated as K) and mean CDA amplitude no matter which group we are looking at. And, last but not least, we have found that we can predict the amount of improvement in the RTS video game by looking at the psychophysiological indices (CDA amplitude) recorded at baseline (before training), but only in the experimental group. We think that the strength of the psychophysiological indicator of VWM capacity might be a marker of the future success in video game acquisition.

Keywords: action video games, visual working memory, trainings, ERPs, EEG

INTRODUCTION

Visual working memory (VWM) allows us to maintain visual information over short periods of time for manipulation or later access (Baddeley, 2003; D'Esposito and Postle, 2015). VWM is an important cognitive function in our daily life and is essential for many higher-level cognitive processes, like problem-solving, learning by observation, or reading (Fukuda et al., 2010;

Shipstead et al., 2012). The capacity of VWM relates to the amount of visual information, which can be maintained in memory simultaneously and accessible if needed (Luck and Vogel, 2013). Previous research (including neuroimaging studies) has shown that VWM capacity is highly limited (Luck and Vogel, 1997; Todd and Marois, 2004), differs across individuals (Rouder et al., 2008), and predicts fluid intelligence in adults (Fukuda et al., 2010; Unsworth et al., 2014). Studies on VWM have relied on a well-established paradigm that measures VWM capacity—the *change detection task* (Luck and Vogel, 1997, 2013), where participant maintains a visual image in memory over a short delay interval and answers if any item (or items) in a later probe image have changed compared to the sample image. The number of items presented (memory load) is manipulated, and performance (working memory capacity, an estimate of the number of items stored in WM measured by K calculated according to Pashler's formula in our study) is compared between trials of different loads. Change detection accuracy mirrors a participant's limitation of VWM capacity and is usually limited to 3–4 items (Vogel and Awh, 2008). It is suggested that the limitation of VWM capacity is associated with visual search and multiple-object tracking performance (Drew et al., 2011; Luria and Vogel, 2011). Previous research has shown that participants with higher VWM capacity are more effective in ignoring unnecessary items during task performance (Vogel et al., 2005). In neurophysiological studies of lateralized VWM, stimuli are presented peripherally, and the subject's task is to attend and maintain in VWM only the items presented in a cued visual hemifield. This generates a lateralized representation, which is larger contralateral compared to ipsilateral of the memorized hemifield, in posterior cortical areas over the retention period that results in a contralateral delay activity (CDA). CDA is a negative slow-wave evoked component that amplitude relates to the number of objects maintained in VWM, so it could be interpreted as a neural index of WM load (Vogel and Machizawa, 2004; Luria et al., 2016). Previous research has shown that CDA amplitude is correlated with memory capacity (Vogel and Machizawa, 2004; Ikkai et al., 2010) and can be modified as a result of WM training (Li et al., 2017). In this study, we used video games as a specific kind of cognitive training having the potential for VWM improvement.

The growing body of research suggests that playing video games enhances the performance on tasks measuring visual and attentional abilities (Green and Bavelier, 2007; Jakubowska et al., 2021). Potential cognitive benefits are possible even with relatively short periods of engagement in playing activity (Green and Bavelier, 2007; Wilms et al., 2013), which makes video games an attractive training option for restoring cognitive functions following brain impairments and in preventive cognitive interventions (Achtman et al., 2008). As there are different kinds of video games, the particular category called action video gaming (AVG) is thought to have a substantial impact on human cognitive functioning. AVG requires players to scan many different complex visual stimuli at the same time and react to multiple stimuli or situations under time pressure (Green and Bavelier, 2003, 2012). AVG is cognitively demanding because of engaging many cognitive functions like working memory, visual attention, and inhibitory control (Green and Bavelier, 2003, 2012). Previous research has shown that long experience in AVG was associated with VWM improvement measured with a change detection task (Boot et al., 2008; Blacker et al., 2014; Li et al., 2015) as well as other tasks (Colzato et al., 2010; Sungur and Boduroglu, 2012; Waris et al., 2019). These results suggest that AVG training may lead to the enhancement of VWM. At the same time, VWM is a key cognitive function in effective video gaming, because it allows players to keep task-relevant visual stimuli over short periods of time for manipulation or later access (Logie, 2011; Blacker et al., 2014). Noteworthy, some studies suggest that cognitive enhancement connected to video game playing does not show far transfer's characteristics (like general improvement in cognitive functioning or learning), but seems to be limited to functions being involved in a given type of video game (Oei and Patterson, 2014).

It is important to note that there are studies that have not found a cognitive improvement after gaming training (Seçer and Satyen, 2014; Dominiak and Wiemeyer, 2016). The possible explanation of these divergent results could be connected to different kinds of games being considered as AVG is actually a broad category with wide inclusion criteria. The study conducted by Dobrowolski et al. (2015) has shown that the achievement of expertise in two different game genres, while both included in AVG category called real-time strategy (RTS) and first-person shooter (FPS), impacts differently cognitive functioning of players. The higher performance in task engaging visual attention and task-switching ability were observed only in RTS (but not in FPS) players as compared to non-players (Dobrowolski et al., 2015). Similarly, RTS experts seem to have higher accuracy and larger VWM capacity than non-experts (Yao et al., 2020). The possible interpretation of these results is that video gaming-related cognitive benefits may depend on the type of actions performed within the game (Dobrowolski et al., 2015). As RTS gaming requires extensive interaction with the complex visual environments, we assume it is highly possible to improve VWM through training with this type of video game. While previous investigations indicate that AVG experts have larger visual attentional capacities, greater capacity of working memory, and higher visual acuity as compared to non-gamers (Green and Bavelier, 2003, 2012; Oei and Patterson, 2013), and that specific AVG can positively affect the level of a given function (Bejjanki et al., 2014; Choi et al., 2020), the impact of the initial level of cognitive functioning on player performance remains largely unexplored.

That is why we decided to use the (RTS) video game StarCraft II with two different types of environments requiring diverse cognitive workloads. Our training types were based on either variable or fixed game environments. The opponent's faction and strategy varied in the variable environment group only (and it was connected to the higher level of difficulty). Our participants were randomly assigned to either a Variable environment, a Fixed environment or the control group. Then it's important to mention that differences between variable and fixed training models were investigated in previous studies, which proved that variable training enhances learning rates and retention, and induce transfer to untrained tasks more, effectively than fixed training (Kramer et al., 1999; Bherer et al., 2008; Erickson et al., 2010). Moreover, training based on a variable environment seems to have more in common—than training with a fixed environment—with people's gaming experiences in everyday life.

The objective of the current study was to investigate the impact of RTS video game StarCraft II training on VWM capacity by comparing training groups' and control group's behavioral (k estimate of WM capacity) and ERP (contralateral delay activity) data in a change detection task. Furthermore we were also interested in whether initial, individual differences in behavioral and psychophysiological indices of VWM can predict the effectiveness of video game training, which could extend our knowledge of the relationship between VWM and in-game performance.

MATERIALS AND METHODS

Participants

A total of 104 participants were recruited online *via* a covert questionnaire (Sobczyk et al., 2015). As a result of: (1) resignation (n = 13); (2) wrong hardware configuration (n = 7); (3) failure to meet all training objectives (n = 6); (4) bad quality of data (n = 7); and (5) lost data (n = 9) only 62 of participants were included in analyses reported here. Participants were randomly assigned to two training groups: with Variable Environment training (VEG; n = 22; 12 males; M_{age} = 25.05, SD_{age} = 2.97), with Fixed Environment training model (FEG; n = 21; 8 males; M_{age} = 25.33, SD_{age} = 3.01), and to two control groups: passive control (PC) group (n = 8; 5 males, M_{age} = 24.63, SD_{age} = 2.97), that did not receive any training and active control (AC) group (n = 11; males = 8; M_{age} = 25.55, SD_{age} = 4.41). The participants played Heart Stone for 30 h (8 h in the laboratory and 22 h at home). As the size of the control groups was inappropriate to analyze them individually, and neither 4 × 2 × 2 repeated measures ANOVAs with Load and Session as the within-subjects factors and Group as the between subject factor, nor One-way ANOVAs with Group as a factor showed any between group differences on behavioral or neurophysiological levels, we decided to merge the groups into one Control group (CG; n = 19; 13 males; M_{age} = 25.16, SD_{age} = 3.80). Then it is important to mention that dropout, which largely contributed to the reduction of the size of the control groups, is a common problem in longitudinal training studies (e.g., Moore et al., 2017). Furthermore, our study employed restrictive recruitment criteria, especially in terms of experience in video game playing, which finally resulted in an inability to re-complete the control groups. All participants reported normal or corrected-to-normal visual acuity, normal color vision and normal hearing. They were right-handed and reported not being on any medications, no history of neurological or psychiatric disorders and injuries, including no previous head trauma, no previous head or neck surgery, and no brain tumors. All participants declared less than 5 h of video games played per week over the past 6 months and no experience with Real Time Strategy or First Person Shooter games. Informed consent was obtained from each participant before the start of the experimental procedure.

Procedure

The study design and the informed consent form were approved by the Ethics Committee of the SWPS University of Social Sciences and Humanities. The research consisted of three steps: (1) Pre-training measurement of cognitive function *via* change detection task (Visual Working Memory task; VWM); (2) Training sessions applied to active groups; and (3) Post-training measurement (**Figure 1**). Experimenters were present during all meetings. Measurement and training sessions took place in the laboratories of the SWPS University in Warsaw.

Experimental Procedure

Prior to the beginning of the experiment, participants were verbally instructed as to what they would be experiencing and were shown what the procedure of EEG electrode mounting entails. Then, after signing a consent form, participants were brought into a laboratory setting and seated in front of a 24 inch BenQ XL2411Z computer monitor (1,920 × 1,080 resolution, 100 Hz refresh rate) at a distance of 60 cm. Electrodes were then mounted and participants were briefly shown the EEG signal and explained how it is affected by eye blinks and muscular movements, which was a part of the procedure aimed at minimizing the number of artifacts in the signal. The procedure was then started, and upon its completion subjects were provided with a place to wash their hair. The entire procedure lasted no more than 2 h and was identical during both measurements. All subjects, who fulfilled training requirements and participated in both measurement sessions, were compensated for their participation with approx. 184 USD after post-training measurement.

Experimental Task—Change Detection Task Paradigm

The experimental task was based on the procedure outlined by Vogel and Machizawa (2004). An initial fixation cross was followed by an arrow, pointing which side of the screen needs to be attended (whether right or left hemifield), after which a pattern (memory array) of two to five colored squares appeared in each hemifield of the screen. The same array appeared again (test array) after a brief retention interval, with a 50% chance that one of the squares in the cued hemifield changed its color. Participants were tasked with detecting changes between the memory and test array by responding with one of the keys (same or different). Square colors were chosen at random from seven possibilities (red, blue, violet, green, yellow, black, white), with the constraint that one color appeared no more than twice in a given test array. Squares (0.65 × 0.65 visual degrees) were randomly positioned at the start of each trial in two 4 deg. × 7.4 deg. hemifields (centered 3 deg. to the left and right of a central fixation, light gray background), with a minimum 2 deg. (center to center) distance between squares. All participants completed 576 trials (144 per load) of the task along with 16 initial practice trials.

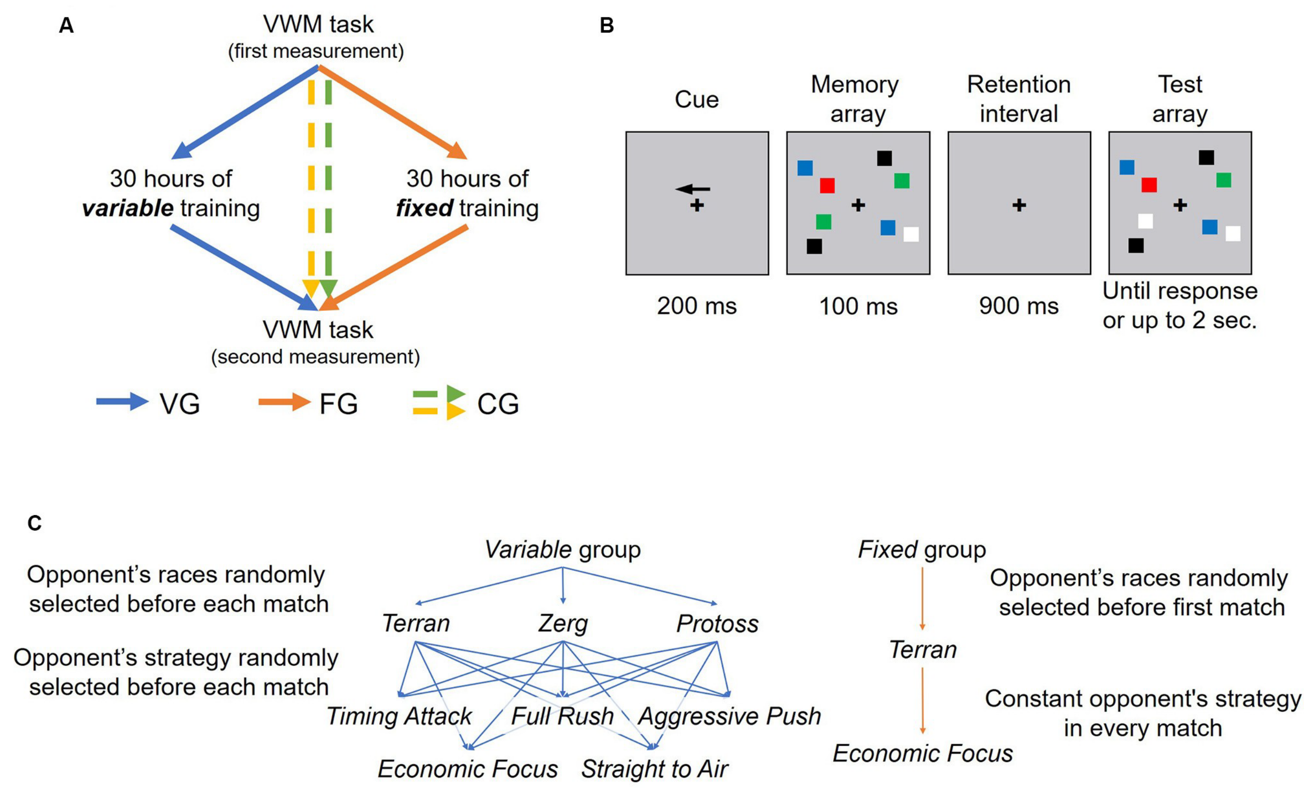

FIGURE 1 | (A) Study design: two measurement sessions were carried out during the study (pre-training and post-training). Training included 30 h of playing in the real-time strategy game (*StarCraft II*), spread over 4 weeks. Training varied depending on the group. The Control group (CG) merges participants from Passive Control, who participated only in the measurement sessions and Active Control, who additionally played Heart Stone for 30 h (8 h in the laboratory and 22 h at home). (B) The visual-working memory task. Participants directed their attention to a cued hemifield (left of right, guided by an arrow at the beginning of each trial) and compared two arrays of colored squares (memory and test arrays) separated by a retention interval. The test array was either identical to the memory array (no-change condition) or differed by one color (change condition). Participants answered whether the two arrays were identical or not. (C) While all of the participants from training groups played as a Terran faction during training, the opponent's race and strategy varied according to the training group type. Participants from the Variable Environment Group (VEG) could match three factions, from each could use one of five strategies. The faction and the strategy were randomly selected before each match for the Variable group. In the case of a Fixed Environment Group (FEG), participants always played against the Terran faction, which used an economic strategy.

Training

StarCraft II Training

The StarCraft II (SC2) training consisted of 30 h of training time over a 4-week period. Training consisted of playing matches (approx. 20 min each) against SC2's artificial intelligence (AI), and all matches were played at our laboratory. Training objectives required the participants to train a minimum of 10 h per week, but no more than 5 h per day. This was done to avoid excessive skew in the distribution of training hours across the training period. There were also two possible training types: Fixed and Variable. The exact differences between the types of training are described below and were presented in **Figure 1**.

Participants had to access an online platform before each match in order to receive configuration parameters; the parameters consisted of the difficulty setting, the opponent's faction, the opponent's strategy, and the game map. Participants from both groups played all of their matches as a Terran faction. While the map was randomly selected from 14 maps before each match in both—Fixed and Variable—training versions, the opponent's faction, and strategy only varied in the Variable group. The Fixed group always faced the same faction (Terran), and their opponent always applied a more passive "Economic Focus" strategy. The Variable group could face any of the three factions (each with their own unique units and abilities) and also any of five opponent strategies: Full Rush, Timing Attack, Aggressive Push, Economic Focus, Straight to Air. The game difficulty was set adaptively for both training types spanning across eight levels (1. Very Easy; 2. Easy; 3. Medium; 4. Hard; 5. Harder; 6. Very Hard; 7. Elite; 8. Cheater) The online platform software recorded the number of wins (+1) and losses (−1) and each time the total passed the multiple of four threshold, the difficulty was increased by one. The difficulty decreased whenever the total dropped below the multiple of four threshold. The training was preceded by an introduction phase designed to familiarize participants with the core concepts of the game and basic gameplay mechanics (see "StarCraft II Introduction" section).

Starcraft II Introduction

The introductory phase consisted of eight parts: (1) a short text describing the goals of the meeting; (2) a text and video-based description of the overall game; (3) a video introduction to the Terran faction, its units and buildings; (4) a text-based description of the fundamental game concepts and in-game interface; (5) an AI guided tutorial that introduces the gameplay in real time, allowing participants to experience the game for the first time; (6) a quiz requiring that the correct labels be attached to each of the five basic unit and building types that are available to the Terran faction, which was intended to check if participants were attentive to the training materials; (7) two films (25 min. each) describing basic strategies and explaining the various stages that each match progresses through; and (8) a three-match series in which the game progressively increased its difficulty, speed, and available units, with no specific guiding instructions. The entire introduction lasted approx. 2.5 h, and did not count into the required 30 h of training. It was also automated and self-paced, with experimenters only providing assistance when needed and also during part 8 of the introduction where assistance was provided to keep up the pace and direction of each training game. Upon completion of this introduction, participants were free to begin training on the following day.

EEG Recording and Analysis

A 64-channel SynAmps RT Neuroscan EEG amplifier and BrainProducts actiCap Ag/AG-Cl active electrode set were used to record brain activity during task performance. All channels were recorded at 1,000 Hz sampling rate. Impedances were held below 5 kΩ. All data were preprocessed offline using MATLAB environment and EEGlab (Delorme and Makeig, 2004), and ERPlab (Lopez-Calderon and Luck, 2014) software packages. The signal was initially re-referenced to a common average and then down-sampled to 250 Hz, followed by a band-pass filter between 0.1 and 40 Hz. Data epochs between −0.2 and 0.996 s were extracted, and all epochs with incorrect behavioral responses were rejected. The remaining epochs were manually filtered for eye-blinks/movements and excessive muscle activity and then averaged.

Data Reduction and Analysis

All analyses were conducted using R Statistical Software (Foundation for Statistical Computing, Vienna, Austria), IBM Corp. Released 2017. IBM SPSS Statistics for Windows, Version 25.0. Armonk, NY: IBM Corp, python and MATLAB custom scripts.

Mixed ANOVAs (3 × 4 × 2) were used to analyze the behavioral and neurophysiological data including the between group variables of group (three levels: CG *vs.* FEG *vs.* VEG) and the within group variables of load (four levels: 2 *vs.* 3 *vs.* 4 *vs.* 5) and session (two levels: pre-training measurement *vs.* post-training measurement). Group comparisons for telemetric data were conducted by a series of t-tests (two-group comparisons). *Post hoc* pairwise t-tests were also performed in case of significant main effects or interactions, with Bonferroni correction for multiple comparisons.

Telemetric data were collected from a total of 5,494 games. While SC2 replays allow obtaining dozens of different variables, participants' expertise or game results do not depend on any particular one. Nevertheless, we selected basic predictor variables that relate to cognitive-motor abilities and game proficiency. We focused on (1) the number of matches played by each player; (2) first army unit creation latency; and (3) first supply collection latency. As better SC2 players play shorter matches, the first of mentioned variables should reflect general players' proficiency. It should be emphasized that the number of played matches positively correlated with the number of won matches ($r = 0.964$, $p < 0.001$) and matches played on more difficult levels (Harder: $r = 0.458$, $p = 0.002$; Very hard: $r = 0.634$, $p < 0.001$, Elite: $r = 0.605$, $p < 0.001$; Cheater: $r = 0.595$, $p < 0.001$), but not easier ones (Very Easy: $r = -0.145$, $p = 0.354$; Easy: $r = -0.146$; $p = 0.351$; Medium: r -0.239, $p = 0.122$; Hard: $r = -0.019$; $p = 0.904$). Then it can be assumed that a higher number of played matches is due to players' higher skills rather than multiple lost matches. Latencies of first army unit creation and first supply collection relate to two key moments in the game environment, which faster execution should result in better performance in the game. We also calculated the overall time each player spent in the game environment which allowed us to confirm the fulfillment of training assumptions. All mentioned telemetric variables were tested for between-group differences by a series of t-tests.

For behavioral data, the capacity of visual working memory, which is measured by the K value, was calculated using the formula proposed by Pashler (1988),

where P(hit) = hits/(hits + misses), and P(FA) = false alarms/(false alarms + correct rejections). In addition to the K values of each set size, we also computed the average K value (K_{mean}) for each participant's visual working memory capacity.

For neurophysiological data, mean amplitudes of CDA (lateralized waveforms; contra−ipsi), averaged across P7/P8 electrodes, from 400 to 900 ms time window were outcome variables (**Figures 4A–C**).

To examine the relationship between behavioral, psychophysiological, and telemetric data, linear regression analyses were conducted.

RESULTS

Telemetric Data

We started by calculating the total time spent in the game and the mean number of played matches for each player. Although there were no significant difference between groups in time spent playing SC2 ($p = 0.513$), participants from Variable group were able to play significantly more matches in that time period (VEG: Mean = 99.68, $SD = 24.782$; FEG: Mean = 85.05, $SD = 14.5$); $t_{(34.152)} = 2.376$, $p = 0.023$ (**Figure 2**). Then we calculated the mean latencies of first army unit creation and first supply collection. Analysis revealed that participants from the Variable group created their army units significantly faster (VEG: Mean = 170.685, $SD = 40.505$; FEG: Mean = 219.243, $SD = 66.683$); $t_{(41)} = -2.901$, $p = 0.006$, but there were no differences in the latency of the first supply collection ($p = 0.696$).

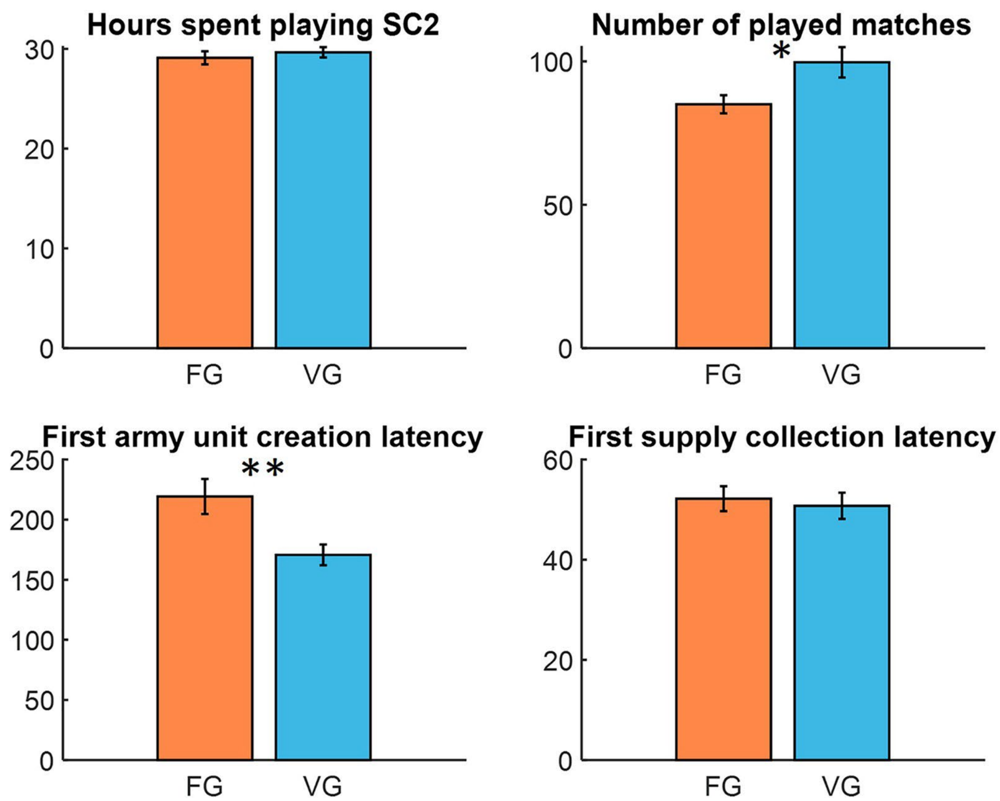

FIGURE 2 | Telemetric variables obtained from the StarCraft II (SC2) environment. While hours spent playing SC2 (upper left) allows us to confirm that both groups (VG: Variable Group; FG: Fixed Group) fulfill training assumptions, other variables indicate players' proficiency. Barplots presenting first army unit creation (lower left) and first supply collection (lower right) give latencies in seconds. Asterisks indicate statistical significance: $^{*}p < 0.05$, $^{**}p < 0.01$.

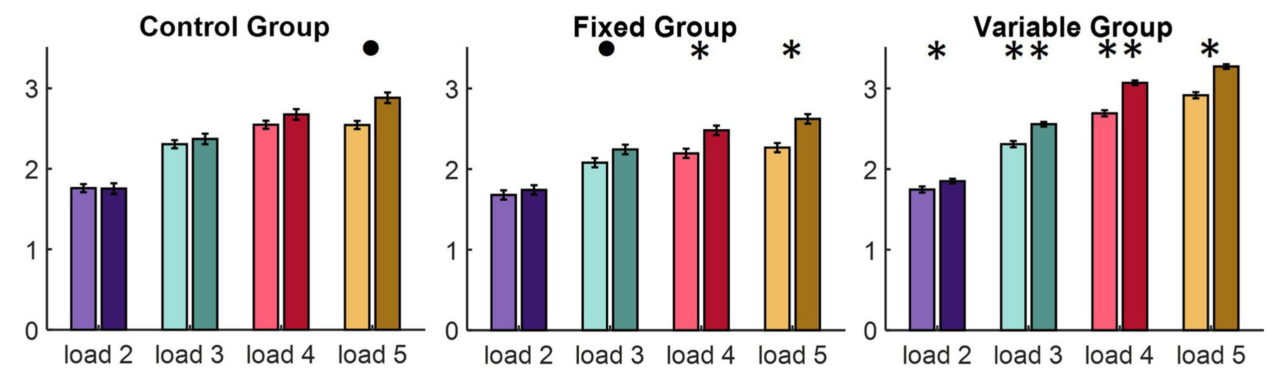

FIGURE 3 | The average K values for each set size in the two tests presented separately for each group. Lighter colors in the pair correspond to the pre-training measurement and darker to the post-training measurement. Asterisks indicate statistical significance: $\cdot p < 0.08$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Behavioral Data

The capacity of visual working memory, measured by the K values, were analyzed using a 4 (Load: load 2 *vs.* load 3 *vs.* load 4 *vs.* load 5) × 2 (Sessions: pre-training *vs.* post-training) × 3 (Group: Control *vs.* Fixed *vs.* Variable) repeated-measures ANOVA, with Load and Session as the within-subjects factors and Group as the between subject factor (**Figure 3**).

Analysis revealed the main effects of Group [$F_{(2, 59)} = 3.209$, $p = 0.048$, $\eta^2 = 0.1$], Load [$F_{(3, 57)} = 134.515$, $p < 0.001$, $\eta^2 = 0.49$], Session [$F_{(1, 59)} = 30.22$, $p < 0.001$, $\eta^2 = 0.07$], Load * Session interaction [$F_{(3, 57)} = 2.808$, $p = 0.039$, $\eta^2 = 0.02$] and Group * Load interaction [$F_{(6, 116)} = 3.992$, $p < 0.001$, $\eta^2 = 0.05$] but no Load * Session * Group interaction [$F_{(6, 116)} = 1.806$, $p = 0.104$, $\eta^2 = 0.085$] or Session * Group interaction [$F_{(2, 59)} = 0.541$, $p = 0.585$, $\eta^2 = 0.018$].

Additional analyses revealed that, while Control group wasn't able to significantly increase its capacity of visual working

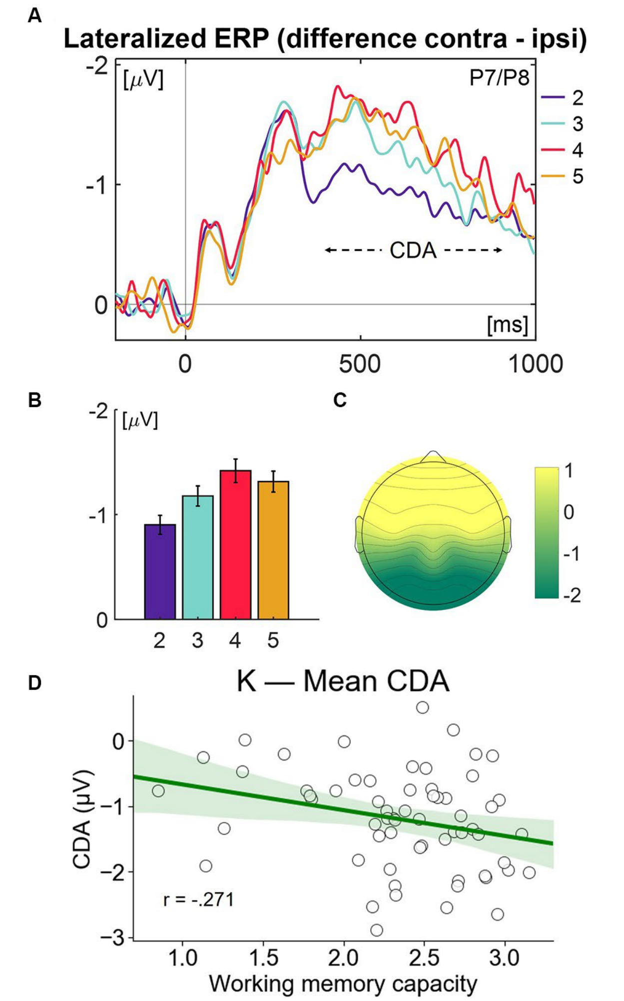

FIGURE 4 | (A) Grand average lateralized waveforms (contra—ipsi), averaged across P7/P8 electrodes, separately for all lateralized target distributions. For statistical analyses of CDA, the mean amplitude from 400 to 900 ms was used. (B) Mean CDA amplitude from 400 to 900 ms, separately for each load. Error bars denote standard errors of the mean, corrected with within-subjects comparisons. (C) Topography of the average activity at each electrode site from 400 to 900 ms. As values were averaged across paired electrodes, the topography is perfectly symmetrical. (D) Scatterplot of working memory capacity (K) averaged across loads and contralateral delay activity (CDA) averaged across loads.

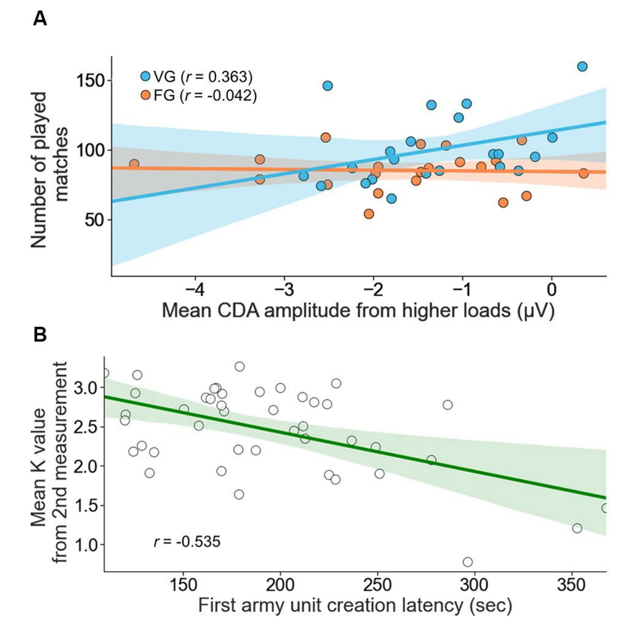

FIGURE 5 | In-game behaviors relationship to psychophysiological and behavioral variables. (A) Initial (from the 1st measurement point) contralateral delay activity (CDA) averaged across loads 4 and 5 predicts the overall number of played matches in the Variable Environment Group (VEG). Observed effect turned out to be insignificant in the Fixed Environment Group (FEG) only. (B) The averaged across training latency of first army unit creation predicts participants' mean K value obtained in post-training measurement. The effect was significant in both groups.

memory at any of used loads, Fixed group increased it at the load 4 ($p = 0.025$) and load 5 ($p = 0.049$) and Variable group was able to significantly increase it at every load (load 2, $p = 0.029$; load 3, $p = 0.008$; load 4, $p = 0.003$, load 5, $p = 0.044$).

Psychophysiological Data

Contralateral delay activity was analyzed using a 4 (Load: load 2 vs. load 3 vs. load 4 vs. load 5) × 2 (Sessions: pre-training vs. post-training) × 3 (Group: Control vs. Fixed vs. Variable) repeated-measures ANOVA, with Load and Session as the within-subjects factors and Group as the between subject factor. Analysis revealed that the only significant effect was the Load effect [$F_{(3, 57)} = 89$, $p < 0.001$, $\eta^2 = 0.288$], but no Session [$F_{(1, 59)} = 0.087$, $p = 0.769$, $\eta^2 = 0.002$], Group [$F_{(2, 59)} = 2.212$, $p = 0.118$, $\eta^2 = 0.02$], Load * Session interaction [$F_{(3, 57)} = 1.336$, $p = 0.272$, $\eta^2 = 0.066$], Load * Group interaction [$F_{(6, 116)} = 0.412$, $p = 0.87$, $\eta^2 = 0.021$] or Session * Group [$F_{(2, 59)} = 0.667$, $p = 0.517$, $\eta^2 = 0.022$].

Psychophysiological, Telemetric, and Behavioral Data Relations

In the next step, we created a model containing a mean contralateral delay activity (CDA) averaged across loads 4 and 5 obtained from pre-training measurement as a predictor, Group as a moderator variable and mean number of played matches as a dependent variable. Created model turned out to be significant [$F_{(3, 39)} = 3.387$, $p = 0.028$, $R^2 = 0.207$] and contained significant influence of the Group [$b = 29.077$, $t_{(39)} = 2.68$, $p = 0.011$] and tendency of interaction between CDA and Group [$b = 10.736$, $t_{(39)} = 1.734$, $p = 0.079$]. Next, it was revealed that while there was no relationship between CDA and number of played matches in the Fixed Group ($p = 0.891$), there was a significant negative relationship in the Variable Group: the smaller initial CDA amplitude averaged from loads 4 and 5, the more matches participants played [one unit decrease in the average CDA component's amplitude resulted in an increase of 10.219 matches played ($t_{(39)} = 2.077$, $p = 0.044$); **Figure 5A**].

In the final analysis, we created a model containing a mean latency of first army unit creation as a predictor, Group as a moderator variable, and mean K obtained from post-training measurement as a dependent variable. Created model turned out to be significant [$F_{(3,\ 39)} = 8.384$, $p < 0.001$, $R^2 = 0.392$] and contained significant influence of the predictor [$b = -0.009$, $t_{(39)} = -2.499$, $p = 0.017$]. Group influence and interaction turned out to be insignificant ($p = 0.349$; $p = 0.12$; **Figure 5B**).

DISCUSSION

The study presented here examined the relationship between the RTS video game proficiency acquired during the training and the improvement of the VWM capacity indexed with behavioral and ERP measures. To properly inspect players' game proficiency, telemetric data from the game environment were used. EEG and behavioral data were collected from non-gamers, who were assigned to one of three groups (Control Group, Fixed Group, and Variable Group).

Participants completed a change detection task, which is the typical experimental paradigm used to examine the VWM capacity, twice during their participation (pre-training and post-training in active groups or over a period of 4 weeks in the passive control group).

The obtained results suggest that VWM capacity improvement was the most significant in the group of participants with the Variable training model. This finding stands in agreement with our initial hypothesis, which assumes that video game influence may vary depending on the training model.

Most importantly, our results show that we can successfully explain game performance by looking at the initial values of the psychophysiological index of VWM and also the behavioral index of VWM (mean K value) at the post-training measurement can be predicted from in-game behavior.

We believe that natural predispositions are an important aspect of achieving success in training, but a good training environment is no less crucial. Therefore, potential players can reach their full potential only under the right conditions. The combination of aspects of natural predispositions and different training models allows for a better understanding of differences in the obtained results, but above all—it shows how important it is to control game environment conditions, which can diversify the gameplay in an enormous number of ways.

VEG Participants Were Able to Achieve the Biggest Improvement of Their VWM Capacity During the Study

The participants from the group with the variable environment training model were able to significantly improve their VWM capacity (measured by Pashler's formula of K value) on each of the tested loads (from load 2 to load 5). This after-training improvement in accuracy stands in agreement with studies, which show that AVG experience is related to VWM abilities (Green and Bavelier, 2003; Boot et al., 2008; Colzato et al., 2010; Clark et al., 2011; Blacker and Curby, 2013; Oei and Patterson, 2013; Li et al., 2015). Still, the Fixed Environment Group had only a significant increase on load 4 and load 5. Then it is important to emphasize that AVG influence corresponds to applied game mechanisms: SC2 matches require players to rapidly switch between multiple sources of action and information in general, but the training's demands were different depending on the training's model. A similar effect was not observed in the control group. Presented results argue that variable training strategies can be more beneficial and allow not only to achieve bigger improvement in specific task but also the occurrence of the far transfer. The fact that VEG players were able to achieve the biggest improvement of their VWM capacity after their training is consistent with this interpretation. In contrast, FEG players were not encouraged to thoroughly explore the game environment, learn different strategies and maximize their various skills, but rather, were trained to repeat one gameplay model in a non-engaging way.

VEG Participants Were Able to Achieve the Biggest Game Proficiency

As mentioned above, three in-game indicators were chosen to measure game proficiency. (1) The number of played matches by each player; (2) latency of creating the first army unit; and (3) first supply collection latency. Telemetric data analysis shows us, even though there were no significant differences in groups about time spent on games, VEG players were able to play significantly more games in that period of time.

In comparison with FEG, VEG participants were significantly faster in creating their first army unit. However, there were no associations between the collection of first supply latency and group types.

These taken into account, we see that comparing with FEG, VEG settings allowed non-gamer participants to be greatly proficient in SC II.

CDA Component, K Value, and Game-Related Factor Analysis

Neurophysiological output was closely analyzed with all parameters using repeated-measure ANOVA. Analyses did not pinpoint significant association either for group type or session. Yet, the load variable had a significant effect on mean CDA amplitudes. This means we observed different CDA amplitudes on different loads. Our data support the notion that CDA is a VWM indicator (**Figure 4D**).

Additionally, the K value had a correlation with CDA. Therefore we understand that low-valued CDA components are significantly associated with both increased VWM capacity and increased input on VWM.

Game Proficiency Indicator Predicts VWM Capacity (K Value)

Two predictive models give us key insights about the relation between game performance, CDA, and K value obtained from the measurements. Model A holds a predictive value about the number of played SC II matches and the mean CDA amplitude on loads 4 and 5 (collected from pre-training session). Participants who have lower initial mean CDA amplitude are less likely to play a higher number of matches, which implies greater natural predispositions to succeed in the game environment. Then it needs to be highlighted that this model was only found to be significant for VEG. It shows that players' natural predispositions can result in better in-game development only in a favorable environment.

Model B enables us to obtain information about participants' level of VWM (K-value obtained from post-training measurement) just by looking at the latency of creating the first army unit. Such a model could help us (in the future) not only to create a rule of thumb for measuring VWM in a specific setting but also to determine players' level of specific cognitive skills in a more natural environment.

Although performed analyzes did not reveal a significant model of moderated mediation, two independent regression models, it's important to interpret obtained results in a broader, common context. As a complex game environment can be reflected by dozens of telemetric variables, which only together make up the full picture of the match and players' skills, it may not be possible to create a simple and efficient model with only one telemetry variable.

Furthermore, initial VWN capacity, measured by K-value, didn't determine in-game performance regardless of the analyzed indicator. Then behavioral results obtained from pre-training measurement cannot be clearly associated with participants' natural predispositions. It should be noted then, that AVG requires more than one cognitive function, so the result of any single behavioral variable may turn out to be insufficient to fully reflect players' in-game proficiency or predispositions.

Presented models, taken together, hold promising results for both: RTS gaming's impact on VWM, and the role of neurophysiological indicators in recognizing the natural predispositions of AVG players. In conclusion, this study confirms that playing RTS games increases VWM capacity. As these improvements were majorly observed in VEG participants (yet still, FEG showed higher results in comparison with the control group), it can be assumed that the intensity of AVG influence depends on the adopted training model. What is more, in the presented study we propose a neurophysiological indicator, which may allow us to identify AVG players with higher predispositions to become better gamers. Last but not least: telemetric data sheds light on game performance, and combining it with other variables *via* regression models holds promising information as such, predicting the capacity of VWM (K-value, scored) from just one game proficiency indicator.

All these findings combined and experimental settings may hold a guiding reference for future research opportunities and commercial usage. Therefore it's important to mention that future investigations should examine a wider range of carefully selected tasks, which can contribute to create a more complete spectrum of cognitive functions and changes that they undergo through VG training.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

ETHICS STATEMENT

The studies involving human participants were reviewed and approved by Komisja ds. Etyki Badań Naukowych Wydziału Psychologii w Warszawie [Ethics committee of Department of Psychology at University of Social Sciences and Humanities]. The patients/participants provided their written informed consent to participate in this study.

AUTHOR CONTRIBUTIONS

NJ: analyzed data, prepared figures, and wrote the first version of the manuscript. PD: designed the study and prepared paradigms' code. IA: helped with EEG data preparation and analysis. MM: collected data. ABr: study conceptualization, data interpretation, manuscript correction, and final approval. All authors contributed to the article and approved the submitted version.

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Video game proficiency predicted by EEG oscillatory indexes of visual working memory.

Video game proficiency predicted by EEG oscillatory indexes of visual working memory.

Natalia Jakubowska[1,2]*, Alicja A. Binkowska[1], Ibrahim V. Arslan[3], Izabela Chałatkiewicz[1], Małgorzata Dąbkowska[1,4], Wiktoria M. Podolecka[5], Paweł Dobrowolski[4], Aneta Brzezicka[1]

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Keywords: theta, alpha, change detection task, cognitive training, RTS

Abstract

While video gaming training may enhance visual working memory (VWM), it is also a key cognitive function for effective video game play. Here, we investigated whether in-game proficiency can be predicted by VWM capacity as indexed by EEG oscillations. Our participants were divided into two training groups that differed in the complexity of the training environment: fixed (FEG) (N=21) and variable (VEG) (N=22), with the second being more challenging. Both groups trained in StarCraft II for 30 hours. EEG data gathering was conducted before and after the onset of training within a change detection paradigm that measures VWM capacity. Initial (pre-training) behavioral and neurophysiological indicators were specified as predictors of in-game advancement, as indexed by variables that were derived from gameplay telemetry (i.e. time series data describing game states and actions). Our main results showed that the initial behavioral and neurophysiological indicators could be used to predict the level of proficiency that our participants achieved during training. Higher levels of the initial alpha power and lower levels of initial theta power were associated with greater in-game results. Interestingly, these effects were stronger for VEG participants with significantly higher in-game advancement. This may show the crucial role of a challenging environment in developing the potential of individual players.

1. Introduction

Visual working memory (VWM) is responsible for temporarily maintaining, storing and manipulating visual information. It is a crucial cognitive ability that allows for conducting multiple actions at the same time (Baddeley, 2003; D'Esposito and Postle, 2015). Previous behavioral and neuroimaging studies have shown that VWM is fairly limited and can only store up to four objects (carrying visuospatial information) at a time, although noticeable differences have been observed between subjects (Vogel and Awh, 2008). Moreover, VWM may act as an indicator of fluid intelligence in adults (Unsworth et al., 2014).

Therefore it is important to mention that, there is an ongoing discussion on the relationship between working memory (WM) and short-term memory (STM) (Aben et al., 2012; Colon et al., 2006). STM is the ability to temporarily store and maintain task-relevant information, which strongly overlaps with WM information storage. The main difference between STM and WM is that WM requires higher attentional control processes in order for the manipulation, updating, and removal of information to occur (Kane et al., 2001). Change detection tasks, such as the one used in our study, are commonly applied to measure VWM capacity. However, it is often used as a visual short-term memory measurement as well due to the mentioned overlap between WM and STM.

Many studies have shown that visual working memory, measured by both: neurophysiological and behavioral indicators, can be improved by various types of training (Li et al., 2017; Wang and Qian, 2021). In a recent study, Guo and colleagues (Guo et al., 2021) found behavioral VWM improvements in participants who underwent a nine day training experiment. The training was based on a tactile orientation sequence task that engaged and enhanced temporal sequence working memory ability. However, another study showed that this improvement (measured by behavioral (K value) and neurophysiological indicators, like P1, CDA or alpha and theta oscillations) may be limited due to its likely stimuli- or task-specificity (Adam and Vogel, 2018). While video games are mainly used for entertainment, a comprehensive review indicates that they may be treated as a form of cognitive training as well (Choi et al., 2020). However, inconsistencies in past research (for instance, a standardized definition of video games and classification criteria for game types) may limit the validity of their assumptions in this regard (Choi et al., 2020).

Recent studies have shown that alpha (8-12 Hz) activity is associated with working memory processes (Moini and Piran, 2020). According to Klimesch, alpha oscillations are involved with unrelated or/and competing information suppression and information selection for a given task, providing a sensory gating mechanism (Klimesch, 2012). In specific,Klimesch indicates that alpha activity is associated with a specific type of encoding stage like early categorization and retrieval of information, which are related to the processing of any kind of meaningful information (Klimesch et al., 2011). In a review by Pavlov and Kotchoubey, the authors remarked that WM load (items kept in WM) influences alpha activity over the posterior areas of the brain. Although the directionality of such an effect differed across studies, for verbal WM, 80% of studies found an increasing effect, while 20%

found a decreasing effect. For visual WM, 60% increasing and 40% decreasing directionalities were observed. Lastly, alpha lateralization was more commonly observed in the right hemisphere (Pavlov and Kotchoubey, 2020).

Even though most study results are limited to associative findings, there are studies that investigated oscillatory activity and WM causally by using different types of transcranial electric stimulation (TES). In a study performed by Riddle et al., the authors found that parietal alpha activity had a causal role in information suppression in WM (Riddle et al., 2020). In the preprint of their paper, Chen et al. (2021) indicated a causal link between alpha power and retention in WM. In the mentioned study, researchers applied transcranial alternating current stimulation (tACS) in both in-phase and anti-phase stages to link these interventions with EEG data but also with behavioral outputs (Chen et al., 2021).

In addition to alpha oscillations, theta oscillations (usually classified within the 4 to 8 Hz range) have been related to WM processes as well. A previous study conducted on rats demonstrated the sequential firing of place cells from the hippocampus in the theta phase, when the animal moved through a space field (O'Keefe and Recce, 1993). Studies focusing on humans have confirmed the relevance of theta activity to spatial navigation (Araújo et al., 2002; Kahana et al., 1999) and other cognitive processes, such as working memory (Onton et al., 2005; Raghavachari et al., 2001; Jensen and Tesche, 2002). Frontal-midline (FM) theta oscillations have been reported in many EEG studies during WM tasks of various task modalities (Onton et al., 2005; Gevins et al., 1997; Jensen and Tesche, 2002), where an increase in memory load is mostly correlated with an increase in FM theta power. However, it is important to mention that some studies show this particular region to display an inverse relationship between theta power and visual working memory capacity (Brzezicka et al., 2019; Ferreira et al., 2019). Further, the oscillation corresponds not only to the memory load dictated by the task itself but also to the individual cognitive demand required to perform it (Zakrzewska and Brzezicka, 2014).

An interesting insight into theta involvement in WM can be seen in studies using transcranial alternating current stimulation (tACS), especially in the right parietal cortex (Bender et al., 2019; Vosskuhl et al., 2015; Wolinski et al., 2018). Slowing down the theta rhythm has been seen to augment performance in verbal STM tasks versus placebo stimulation. Wolinski et al. (Wolinski et al., 2018) compared three groups receiving 4 Hz, 7 Hz and placebo frequency stimulation, with results indicating better visuospatial task performance mainly in the visual hemifield contralateral to the 4 Hz stimulation. These results are in line with previous research, where more gamma cycles can be nested in slower theta waves; therefore, more items can be retained. A recent review compared two theoretical approaches to theta-gamma coupling regarding visual working memory storage load (Sauseng et al., 2019). The already described classic *slot model* view supports the idea that WM capacity is limited to three or four items. However, a contradictory theoretical framework known as the *cognitive resource model* has been suggested by Bays and Husain (Bays and Husain, 2008), suggesting not the amount of items as the most important factor but the need for cognitive resources to retain the wanted information. In this model, a portion of cognitive resource is distributed for each of the items stored in memory , resulting in a variable fidelity of retaining information depending on the number of items being stored. According to the slot model, gamma waves are meant to code multiple WM items being nested in theta cycles (Lisman and Idiart, 1995; Freunberger et al., 2011). Additionally, in line with the cognitive resource model, needing to retain fewer items leads to a longer gamma burst and thus a slower theta wave, resulting in a higher fidelity memory representation.

Inhibition of unrelated information is a crucial aspect of not only WM but also video game proficiency. Inhibition of non-task-related stimulus processing may be necessary to perform a visual scanning task with high efficiency. According to Klimesch, task relevant activation processes in memory are not interfered with by the activation of unrelated neuronal structures because unrelated structures are inhibited by an increase in alpha power (Klimesch et al., 2011). However, Sauseng showed that the retention of related information and inhibiting of irrelevant information rely on independent neutral substrates (Sauseng et al., 2009). This is necessary to achieve high performance in activities like video game play because VWM has a limited capacity (Luck and Vogel, 1997; Todd and Marois, 2004). While memory capacity relies on effective suppression of unrelated information (Vogel and Machizawa, 2004), a game like StarCraft II (SC2) already strains attentional resources due to multitasking demands, and therefore may place further emphasis on the effective use of VWM (Jakubowska et al., 2021).

A recent study on action video games (AVG) took a closer look at alpha power, using a covert questionnaire to recruit AVG players and non-video game players (NVG). Researchers tested VWM capacity through a specifically designed ‘theory of visual attention’ paradigm, finding a positive association between information processing time and posterior alpha power within the range of 10 and 12 Hz. Additionally, it was found that this association was modulated positively by being an AVG player. This means that, in comparison to NVG players, AVG players are faster in information processing and exhibit larger alpha power than NVG players (Hilla et al., 2020).

In the case of the current study, previous research showing that playing video games can enhance working memory performance, including VWM, are of particular interest (Colzato et al., 2013; Oei and Patterson, 2013; Blacker et al., 2014; Jakubowska et al., 2021). Playing video games can also have a positive effect on visual STM, as video game players have been shown to surpass non-video game players in remembering complex and intricate information (Blacker and Curby, 2013). However, it should be noted that there are also video game training studies in which no cognitive improvements were observed (Seçer and Satyen, 2014; Dominiak and Wiemeyer, 2016).

Each video game, even if classified to a particular game genre, has its own unique characteristics and mechanics. Baniqued et al. (2013) propose to classify video games depending on the engagement of cognitive, emotional, or social processes (Baniqued et al., 2013). A clear taxonomy of video game genres is vital for research on their cognitive and neuropsychological impact (Bavelier and Green, 2019).

AVG have gained substantial research interest, as they require the engagement of many cognitive functions, including WM, inhibitory control, and visual attention (Green and Bavelier, 2003, 2012). The AVG category is broad, but includes mainly first-person shooter

(FPS) and third-person shooter (TPS) games. Colzato et al. found that video game players are more competent when deciding which information to retain during working memory tasks, and more efficient in disposing unnecessary information, than non-video game players (Colzato et al., 2013). Their study also showed that playing FPS games is correlated with better WM updating and monitoring. Another study (Blacker et al., 2014) compared two groups: a training group in which participants played Call of Duty (a FPS game) and a control group in which participants played The Sims 3 (a life-simulation type game). None of the participants had previous experience playing video games. VWM capacity increased significantly in the training relative to the control group, likely due to the more cognitively demanding nature of FPS games.

Besides FPS and TPS, Real-Time Strategy (RTS) games are often mentioned as AVG subtypes. In RTS games, the player has a top-down view of the world (instead of a first-person perspective as in FPS games) and must control various in-game aspects simultaneously, such as collecting and spending resources and managing units during battle. FPS games are mainly focused on shooting at targets (Dobrowolski et al., 2015). Due to these differences, and a strong habit derived from commercial definitions, advanced RTS games are recently more often assigned to various categories, which excludes shooter games - leaving them as a classic AVG.

For this study we chose to use the RTS game Starcraft II. SC2 has a rich task environment and engaging characters, but also has the advantage of offering multiple levels of mastery and a wide range of tasks that require the player to focus on many pieces of information at the same time (Jakubowska et al., 2021). This requires the engagement of multiple cognitive domains to achieve success, such as decision making, perception, motor skills, and attention (Thompson et al., 2013). As an RTS game, SC2 may improve various aspects of VWM and WM. Playing RTS type games may enhance other cognitive functions as well. They may lead to greater cognitive flexibility (Glass, et al, 2013; Nuyens, et al, 2019), as well as better performance during tasks requiring multiple object tracking and task switching (Dobrowolski, et al, 2015).

To better understand the relationship between VWM and in-game performance, we decided to focus on established neurophysiological indicators of visual working memory - neural oscillations in the theta and alpha frequency range (Pavlov and Kotchoubey, 2020).

Knowing the possible influence of VWM capacity on performance in real-time strategy games like SC2 and its neurophysiological indicators, the objective of the current study is to investigate whether in-game proficiency can be predicted based on neural oscillatory dynamics during a change detection task and VWM capacity (Vogel and Machizawa, 2004). We decided to use change detection as a well-established measure of VWM capacity. We first test our participants with this change detection task, then we train our participants as divided into two groups where they will differ in terms of training complexity in an effort to observe any dependencies: a fixed environment training model (FEG) and a variable environment training (VEG; more complex) model were defined for this aim. Simply put, VEG is widespread and altering (opponent, scenario) while FEG is static and constant (opponent and scenario) SC2 gaming training. However, it is important to mention that the difficulty level varied across both groups in accordance with their proficiency gained during training (for further details: section 2.3 *Training Models*). We hypothesize that alpha and theta powers will be associated with WM load retention capacity that is obtained through post-training change detection task in accordance to training types. Our rationale behind is, previous research conducted by Mathewson and colleagues (Mathewson et al., 2012) has shown that pre-training frontal EEG alpha and delta power associated with cognitive control can predict learning rate and skill improvement in a complex video game. Since alpha power is associated with unrelated information suppression (Riddle, 2020) and WM retention (Chen et al.) (which are crucial for video game performance), we hypothesize that increased alpha will relate to better game proficiency. Furthermore, there are contradictory results regarding theta power, although in accordance with evidence gathered in the comprehensive review by Sauseng and colleagues; we hypothesize that theta power will be increased with higher WM capacity (Sauseng et al., 2010). Given the literature mentioned in the presented introduction, we suggest that there is a bilateral, positive relationship between WM and level of proficiency that participants can achieve during video game training.

In short, while VWM has a critical value in video game performance, video game training can also influence VWM. In the context of the current investigation, we expect that SC2 training will have a strong influence on VWM by enhancing information retention. Specifically, we expect the initial (pre-training) FM theta power and increase in posterior alpha power that is related to VWM capacity to predict the in-game proficiency of our participants. The use of complex telemetry variables (e.g. perception action cycle [PAC], player's units variability) in order to infer about persons' current state of gaming proficiency is something new in the research on the psychophysiological correlates and predictors of the in-game behavior. It also reflects the advancement in our understanding of this relationship since we have published our first set of analysis on this topic (Jakubowska et al., 2021).

2. Methods

2.1. Participants

Participants were randomly assigned to one of two groups: Fixed Environment Group (n = 21, 8 males, M_{Age} = 25.83, SD_{Age} = 3.22, $M_{Years\ of\ education}$ = 16.5, $SD_{Years\ of\ education}$ = 2.09) and Variable Environment Group (n = 22, 11 males, M_{Age} = 25.24, SD_{Age} = 3.01, $M_{Years\ of\ education}$ = 16.45, $SD_{Years\ of\ education}$ = 1.95). These participants are a subset of a larger sample that was used and presented in detail in our previous study (Jakubowska et al., 2021). Presented samples are final and were included in all of the following analyses.

We calculated post hoc power using MorePower 6.0 (Campbell & Thompson, 2012) with the following inputs: repeated measures design, total sample size: 43, number of groups: 2, number of measurements: 8, alpha level: 0.05, and eta square = 0.095 (we defined different eta squares, depending on the dependent variable). With these input parameters the power of our study was estimated at 0.8 or above.

All participants were right-handed, reported playing less than 5 hours of video games per week, and had no prior experience in playing RTS, FPS or TPS games. Each had corrected to normal vision, normal color vision and no hearing impairments, no history of psychiatric or neurological disorders or injuries, and no previous head trauma. Informed consent was obtained from each participant prior to the start of the experimental procedure.

The Ethics Committee of the SWPS University of Social Sciences and Humanities approved the informed consent form and the study design, which was divided into three separate parts. First, the participants performed a change detection task (Visual Working Memory task; VWM) to measure their cognitive functioning before training. The second part involved the groups undergoing training sessions. Finally, participants took part in a post-training measurement. Experimenters were present during all training sessions and measurements, which took place in the laboratories of SWPS University in Warsaw. All participants gave written informed consent in accordance with the Declaration of Helsinki before the first measurement session. All experiments were performed in accordance with the approved guidelines and regulations. Every participant was compensated for fulfilling the training requirements and participating in the two measurement sessions with approximately 184 USD.

2.2. Experimental task - change detection paradigm

After signing a consent form, participants were brought into a laboratory setting and seated in front of a 24-inch BenQ XL2411Z computer monitor (1920 x 1080 resolution, 100 Hz refresh rate) at a distance of 60 cm. The experimental task used during the study was based on the procedure created by Vogel and Machizawa (Vogel and Machizawa, 2004).

As the EEG activity was measured during the procedure, participants were asked to look at the fixation point during the whole procedure, trying not to move their eyes rapidly or blink during stimulus presentation. During the whole procedure, chinrest was used to stabilize the head position and limit unconscious head movements.

After the initial fixation cross, an arrow appeared pointing either to the right or left hemifield to cue participants towards on the target hemifield. This was followed by 2 to 5 differently coloured squares (memory array), referred to as load, appearing on both sides of the screen. After a brief retention interval, a test array identical in spatial distribution to the memory array was presented. There was a 50% chance that the color of one square in the cued hemifield changed. The task involved detecting changes between the test and the memory array, which was done by pressing a key corresponding to either a ‘same’ or ‘different’ response. The colors of the squares were randomly chosen from seven possibilities (red – RGB: 255 0 0, blue – 0 0 255, violet – 238 130 238, green – 0 258 255 0, yellow – 255 255 0, black – 0 0 0, white – 255 255 255). A color could only appear once in a given hemifield (per trial). Squares (0.65 x 0.65 visual degrees) were randomly positioned at the start of each trial within two 4 deg. x 7.4 deg. hemifields (centered 3 degrees to the left and right of the central fixation, light gray background), with a minimum 2 deg. (center to center) distance between squares. All participants completed 576 trials (144 per load) of the task along with 16 initial practice trials. The specific structure of the procedure is presented in Figure 1.

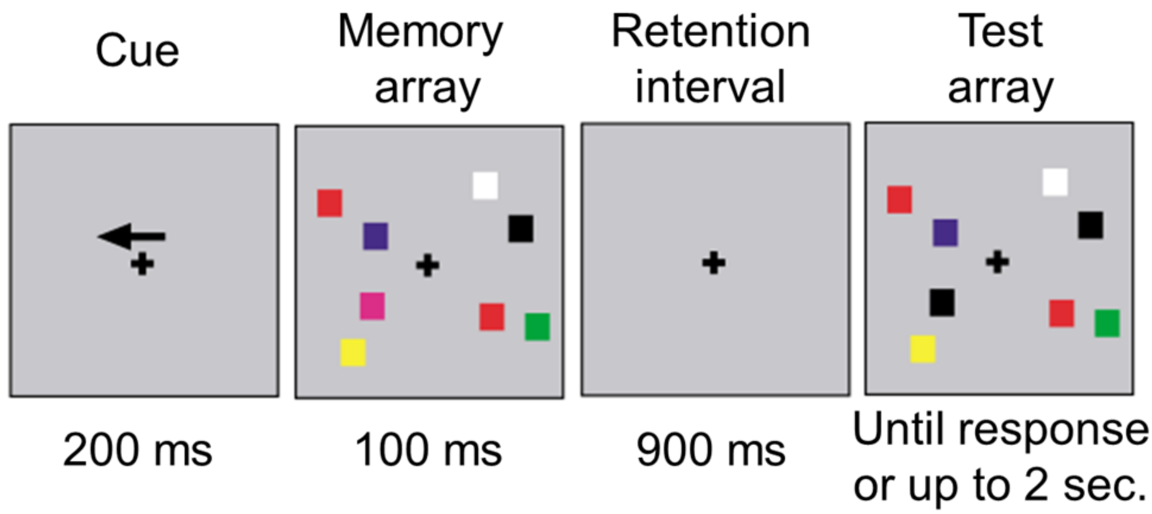

FIGURE 1 | The visual-working memory task. Participants directed their attention to a cued hemifield (left or right, guided by an arrow at the beginning of each trial) and compared two arrays of colored squares (memory and test arrays) separated by a retention interval. The test array was either identical to the memory array (no-change condition) or differed by one color (change condition). Participants answered whether the two arrays were identical.

2.3. Training Models

As Sun and colleagues (2018) indicates, SC2 is widely considered as the most challenging RTS game. The underlying challenges include a large observation space, a continuous and infinite action space, limited field of view, simultaneous moves for all players, and long-horizon delayed rewards for local decisions (Sun et al., 2018). Overall, the player is required to build a virtual base and army to attack and overcome their opponent. In 1 versus 1 matches, players need to focus on three main aspects of gameplay: (a) optimal resource gathering, (b) expanding, protecting, and engaging production potential, and (c) managing army composition and actions (Kowalczyk et al., 2018).

SC2 gameplay is based on three playable races (Terran, Zerg, and Protoss), each of which has unique units and abilities and requires a different playstyle to optimize performance. Apart from the possibility of playing against other players, there are ten built-in levels of AI script difficulty for custom games: Very Easy, Easy, Medium, Hard, Harder, Very Hard, Elite, and three different Cheater options. In addition, five different AI strategies are available (1. Full rush, 2. Timing Attack, 3. Aggressive Push, 4. Economic Focus, 5. Straight to air). These strategies allow the AI to make high-level decisions so that it can attack the player in specific ways. The implemented difficulty levels and combat styles allow players to get to know a variety of gameplay possibilities and general game mechanics. It should be emphasized that playing against AI is usually treated as an introduction and a way to prepare a new player to play against other players.

SC2 gives players the opportunity to re-watch their matches, which is commonly used to analyse their strengths and weaknesses. More importantly, thanks to tools such as sc2reader (a Python library), it is possible to extract telemetric variables from the matches. These data represent basic gameplay information (e.g. match length, match result, information about the players), typical game indicators like APM (Actions per minute), PACs (Perception Action Cycles; refers to number of independent map areas at which actions are performed), PAC latency (latency to first action in a PAC), usage of hotkeys (keyboard shortcuts to certain actions), and also specific economic data (e.g. the amount of gathered/spent resources), key events (e.g. creation or loss of key buildings and units), and the specific time at which individual actions and events took place. Knowing the values of individual telemetric variables and the rules that are applied in the game, it is possible to draw objective conclusions about the level of a player's advancement. Therefore, higher values of such variables will characterise better players (Glass et al., 2013).

Lastly, it should be noted that the mentioned variables, though commonly used to monitor game achievements and progress, best reflect the development of new players. The variance in such performance metrics naturally decreases with expertise.

SC2 training was divided into a four-week period, with a total of 30 hours of gameplay. This training entailed playing SC2 matches (approximately 20 minutes per match) against AI. Training regulations required that participants train a minimum of 10 hours per week, but no more than 5 hours per day. This approach was implemented to avoid excessive skew in the distribution of training hours. All matches took place in our laboratory. As mentioned previously, the exact training experience depended on the training group (FEG or VEG). The details are depicted in Figure 2.

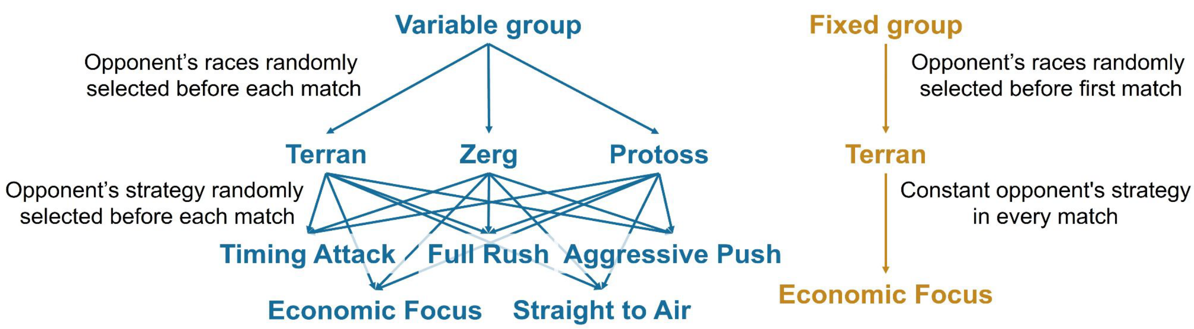

FIGURE 2 | All participants played the Terran faction during training. However, the strategy and race of the opponents varied according to the type of group. While Fixed Environment Group (FEG) always played against the Terran faction using the economic strategy, the Variable Environment Group (VEG) could match three factions, and each could use one of the five play strategies. The faction and strategy types were randomly assigned before each match in VEG.

Before each match, participants had to log into an online platform to receive configuration parameters. These parameters were difficulty level, opponent faction and strategy, and the game map. As the Terran faction is considered the easiest to learn among SC2 players, both groups played all matches as Terrans. Before each match, the map was randomly assigned out of 14 possible options for both the FEG and VEG. However, the opponent's faction and strategy only differed for the VEG. The FEG always played against the same Terran faction, which implemented a passive “Economic Focus" strategy. “Economic focus” strategy imposes a slightly slower gameplay course, as AI is preparing for a long match, and can therefore be interpreted as easier than others, especially in the early stages of game learning. Along with the experience gained from subsequent matches, players should therefore see in that a chance to quickly defeat the opponent.

The VEG was exposed to a greater variety of settings. The opponent’s faction (each with their special units and abilities) was randomly assigned for each match, as was their strategy (out of five possibilities). Lastly, game difficulty was set adaptively for both training types, spanning eight levels. The difficulty level increased when the sum of wins (+1) and losses (-1) passed a threshold of 4. Difficulty decreased when the threshold dropped below 4. Before the training phase began, an introductory phase (guided by an experimenter) was implemented to familiarize participants with the core concepts and gameplay mechanics.

2.4. EEG recording and analysis

A 64-channel SynAmps RT Neuroscan EEG amplifier and a BrainProducts actiCap Ag/AG-Cl active electrode set were used to record brain activity during both (pre- and post-training) change detection task performances. All channels were recorded at a 1000 Hz sampling rate. The impedances were kept below 5 kΩ. The FCz electrode was used as an online reference electrode. No online filters or EOG were used during measurements. All data were pre-processed offline using the MATLAB 2019a environment, EEGlab 2020.0 (Delorme and Makeig, 2004) and ERPlab 8.02 (Lopez-Calderon and Luck, 2014) software packages. The signal was initially re-referenced to a common average and then down-sampled to 250 Hz, followed by a bandpass filter between 0.1 and 40 Hz. Independent component analysis (ICA) was applied to remove ocular artifacts. Data epochs between -0.2 (with 0 being the presentation of the memory array) to the end of the retention period (1200 ms: memory and retention period serving as a source for power extraction) were extracted. All epochs with incorrect behavioral responses were rejected. Epochs were then inspected visually and those still heavily affected by artifacts were discarded. Specific number of removed epochs can be found in the Supplementary Table 1. A 200-ms baseline correction was applied (from 200 ms before memory array presentation to 0).

We calculated Log Power Spectral Density $10 * \log_{10}(\mu V^2/Hz)$ via *Welch's* Method from 1 second of the epoched signal (with 0 being the memory array presentation). We estimated the log power spectral density for each electrode and each subject separately for each memory load (2, 3, 4, or 5). Power spectra had a frequency resolution of 1 Hz and were computed one second after the presentation of the memory array (100 ms of memory array presentation + 900 ms of retention time). Then, the 1/f neural noise was removed (Donoghue et al., 2020). Electrodes for frontal theta and posterior alpha were chosen a priori from the literature (Adam et al., 2018) and based on the topographical maps (Supplementary Figure 1). Frontal theta was calculated as the average of theta power (4-8 Hz) from electrodes F3, F4 and Fz. Posterior alpha power (8-12 Hz) was calculated as the average of electrodes O1, P3 and PO3 for the left cluster, and O2, P4 and PO4 for the right cluster.

2.5. Statistical Analysis

All analyses were conducted using R version 4.0.4 statistical software (Foundation for Statistical Computing, Vienna, Austria), IBM SPSS Statistics for Windows Version 25.0, and Python 3.7.1 and MATLAB 2019a custom scripts.

Telemetric data were extracted from a total of 5475 games using sc2reader version 1.8.0 and PACAnalyzer Python libraries. Using the SC2 replays, we are able to collect a vast number of different variables. Importantly, the proficiency of gameplay does not depend on a specific one. Nevertheless, we specified 27 pre-chosen fundamental predictors that relate to game proficiency and cognitive-motor abilities. As we did not want to focus on all of them but rather only those that were most predictive of performance, we applied multiple logistic regression (implemented by sklearn python library) to choose only variables that significantly predicted match results.

Multiple logistic regression indicated that match length [$\beta = 0.0008$, $p < 0.001$, 95% CI (0.000, 0.001)], units variability [$\beta = -0.15$, $p = 0.019$, 95% CI (-0.186, -0.114)], first supply event time [$\beta = 0.0059$, $p = 0.019$, 95% CI (0.001, 0.011)], first army creation event time [$\beta = -0.0049$, $p < 0.001$, 95% CI (-0.006, -0.004)], extracting-spending minerals ratio [$\beta = -0.2544$, $p = 0.006$, 95% CI (-0.436, -0.073)], player's average PAC latency [$\beta = 0.5125$, $p < 0.001$, 95% CI (0.315, 0.710)], and difficulty level [$\beta = -0.5348$, $p < 0.001$, 95% CI (-0.600, -0.470)] were the most accurate predictors of match result.

Although better SC2 players play short-duration matches, basic variables should reflect a player's proficiency in general. The number of played matches was positively correlated with the number of matches won ($r = 0.964$, $p < 0.001$) and matches played on more difficult levels (Harder: $r = 0.458$, $p = 0.002$; Very hard: $r = 0.634$, $p < 0.001$, Elite: $r = 0.605$, $p < 0.001$; Cheater: $r = 0.595$, $p < 0.001$) but not easier ones (Very Easy: $r = -0.145$, $p = 0.354$; Easy: $r = -0.146$; $p = 0.351$; Medium: r -0.239, $p = 0.122$; Hard: $r = -0.019$; $p = 0.904$). With this in mind, we assume that a greater number of matches played can be attributed to better performance by participants rather than to lost matches.

More detailed information about between-group differences calculated on excluded telemetric variables can be found in Supplementary Figures 2 and 3.

We also calculated the overall time each player spent in the game environment, which allowed us to confirm whether our training assumptions (duration) were met. All mentioned telemetric variables were tested for between-group differences by a series of t-tests.

For behavioral data, the capacity of visual working memory (K) was calculated using the formula proposed by Pashler[58], K = setsize × (P(hit) ÷ (1 – P(FA)), where P(hit) = hits/(hits + misses), and P(FA) = false alarms/(false alarms + correct rejections).

As the presented results constitute only a part of the actual data that was collected for a larger-scale project, a detailed analysis of the behavioral data, including an additional control group and its interpretation in relation to the EEG and telemetric results, can be found in a paper by Jakubowska and colleagues (Jakubowska et al., 2021).

3. Results

3.1. Behavioral results

The capacity of visual working memory, as measured by K values, was analyzed using a 4 (Load: load 2 *vs.* Load 3 *vs.* Load 4 *vs.* Load 5) × 2 (Sessions: pre-training *vs.* post-training) × 2 (Group: FEG *vs.* VEG) repeated-measures ANOVA, with Load and Session as the within-subject factors and Group as the between-subject factor. The analysis revealed main effects of Group [$F(1, 41) = 12.955$, $p = 0.011$, $\eta^2 = 0.147$], Load [$F(3, 39) = 73.735$, $p < 0.001$, $\eta^2 = 0.850$], Session [$F(3, 39) = 13.887$, $p < 0.001$, $\eta^2 = 0.253$], a Load × Group interaction [$F(3, 39) = 3.027$, $p = 0.041$, $\eta^2 = 0.189$], and a Load × Session interaction [$F(3, 39) = 5.030$, $p = 0.005$, $\eta^2 = 0.279$], but no Session × Group interaction [$F(1, 41) = 0.170$, $p = 0.683$, $\eta^2 = 0.004$] or Load × Session × Group interaction [$F(3, 39) = 0.169$, $p = 0.917$, $\eta^2 = 0.013$]. All specific K values are presented in Table 1. The individual effects are shown and described in Figure 3. Additional barplots presenting changes in the K value can be found in Supplementary Figure 4

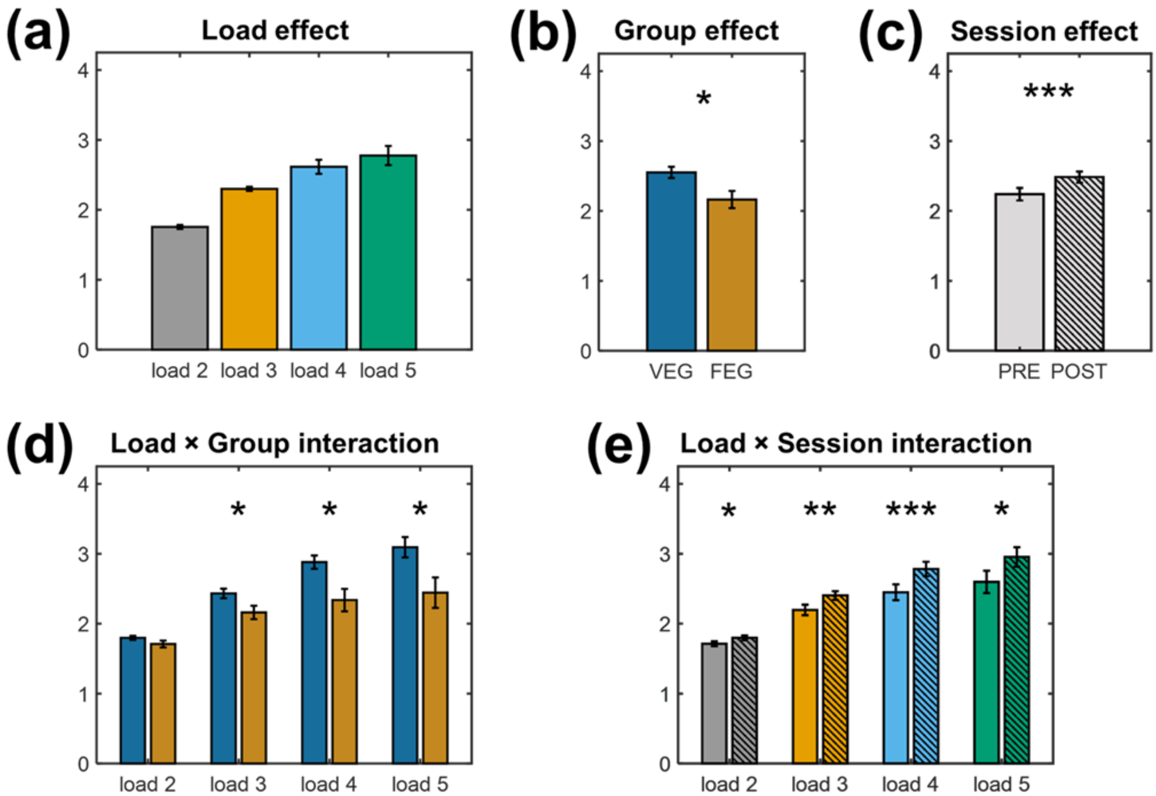

FIGURE 3 | The average K values (Y-axis) for individual effects. Asterisks indicate statistical significance: * p < 0.05, ** p < 0.01, *** p < 0.001. **(a)** Bonferroni corrected comparisons revealed that K value at load 2 was significantly lower in comparison to load 3 (p < 0.001), load 4 (p < 0.001), and load 5 (p < 0001). Load 3 turned out to be significantly lower compared to load 4 (p < 0.001) and load 5 (p < 0.001). No other significant differences were observed. **(b)** Analyses revealed that the Variable Environment Group (VEG) had significantly higher K values in comparison to Fixed Environment Group (FEG) ($p = 0.011$). **(c)** Participants significantly increased their K values from the pre-training (PRE) to the post-training measurement (POST) ($p < 0.001$). **(d)** Bonferroni corrected comparisons revealed that the VEG had a significantly higher K value at load 3 ($p = 0.025$), load 4 ($p = 0.005$) and load 5 ($p = 0.016$) in comparison to the FEG No significant differences at load 2 ($p = 0.122$) were observed. The blue bars (presented on the left side of each pair) represent VEG, and the orange bars (on the right side) FEG. **e)** Bonferroni corrected comparisons revealed that participants were able to significantly increase their K value at load 2 ($p = 0.025$), load 3 ($p = 0.003$), load 4 ($p < 0.001$), and load 5 ($p = 0.005$). Bars presented on the left side of each pair represent pre-training measurement. Hatched bars on the right side - post-training measurement.

3.2. Psychophysiological results

First, repeated-measures ANOVAs with load (four levels: 2 *vs* 3 *vs* 4 *vs* 5) and session (two levels: pre-training measurement *vs* post-training measurement) as within-subject factors and group (two levels: FEG *vs* VEG) as a between-subject factor were performed on the mean alpha power (8-12 Hz, averaged across electrodes O1, O2, P3, P4, PO3, PO4, obtained from 1 second after memory array presentation).

ANOVA revealed significant effects of load [F(3, 39) = 4.766, $p = 0.006$, $\eta^2 = 0.268$] and session [F(1, 41) = 6.624, $p = 0.014$, $\eta^2 = 0.130$], but no effects of group [F(1, 41) = 0.597, $p = 0.444$, $\eta^2 = 0.014$], load × group interaction [F(3, 39) = 0.671, $p = 0.575$, $\eta^2 = 0.049$], load × session × group interaction [F(3, 39) = 1.064, $p = 0.375$, $\eta^2 = 0.076$], or group × session interaction [F(1, 41) = 0.272, $p = 0.605$ $\eta^2 = 0.007$].

All specific alpha values are presented in Table 2. Individual effects are shown and described in Figure 4. Additional barplots presenting changes in the alpha power can be found in Supplementary Figure 4.

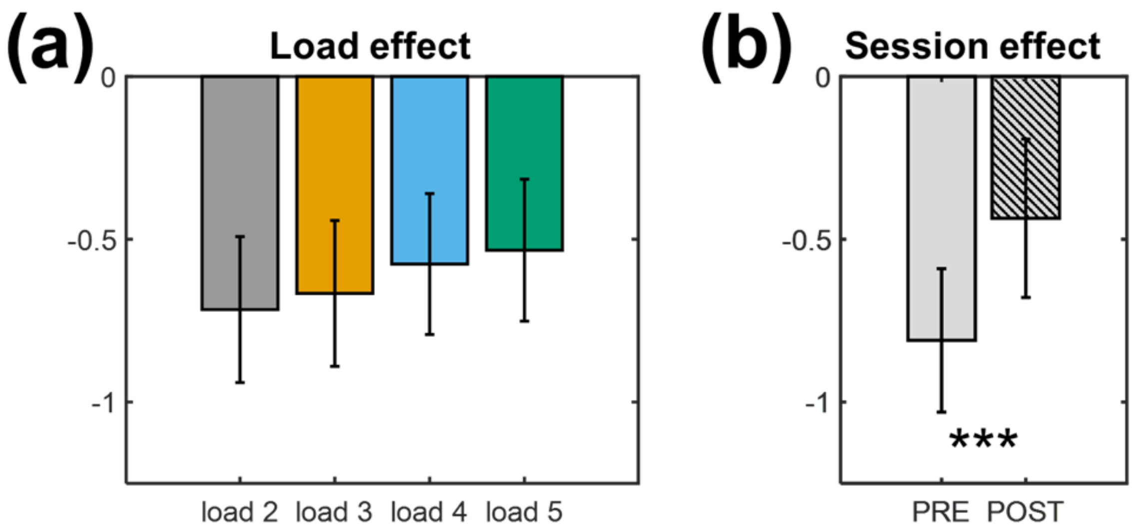

FIGURE 4. | Average alpha log power spectral density 10 * $\log_{10}$ ($\mu V^2/Hz$) (Y-axis) for individual effects. Asterisks indicate statistical significance: *** $p < 0.001$. **(a)** Bonferroni-corrected comparisons revealed that the alpha power at load 2 was significantly lower compared to load 4 ($p = 0.004$) and load 5 ($p = 0.008$). No other significant differences were observed. **(b)** Participants significantly increased their alpha power from the pre- (PRE) to post-training measurement (POST) ($p = 0.014$).

Then, repeated-measures ANOVAs with load (four levels: 2 *vs* 3 *vs* 4 *vs* 5) and session (two levels: pre-training measurement *vs* post-training measurement) as within-subject factors and group (two levels: FEG *vs* VEG) as a between-subject factor were performed on the mean theta power (4-8 Hz, averaged across electrodes Fz, F3, F4, obtained from 1 second after memory array presentation).

ANOVA revealed significant effects of load [$F(3, 39) = 6.494$, $p = 0.001$, $\eta^2 = 0.333$], session [$F(1, 41) = 63.376$, $p < 0.001$, $\eta^2 = 0.607$], group [$F(1, 41) = 14.536$, $p = 0.045$, $\eta^2 = 0.094$], load × session [$F(3, 39) = 6.485$, $p = 0.001$, $\eta^2 = 0.333$] and session × group [$F(1, 41) = 16.967$, $p < 0.001$, $\eta^2 = 0.293$], but no load × group interaction [$F(3, 39) = 0.525$, $p = 0.668$, $\eta^2 = 0.039$] or load × session × group interaction [$F(3, 39) = 2.170$, $p = 0.107$, $\eta^2 = 0.143$].

All specific theta values are presented in Table 3. The individual effects are shown and described in Figure 5. Additional barplots presenting changes in the theta power value can be found in Supplementary Figure 4

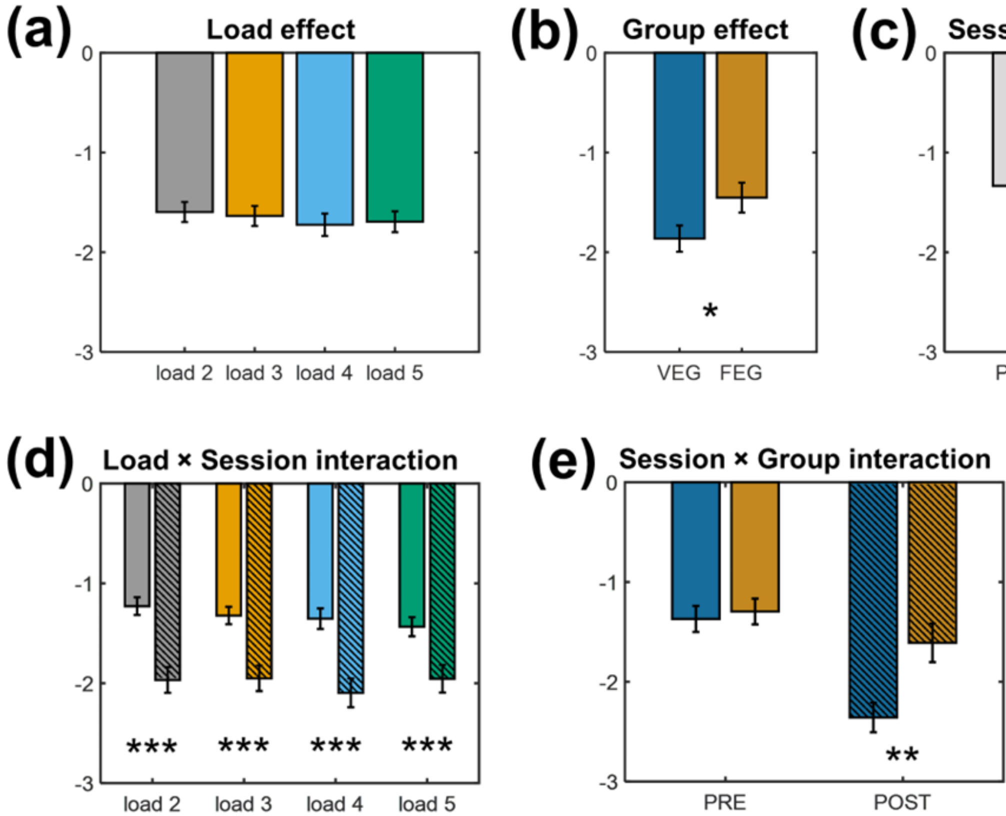

FIGURE 5. | Average theta log power spectral density 10 * $\log_{10}$ ($\mu V^2/Hz$) (Y-axis) for individual effects. Asterisks indicate statistical significance: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. **(a)** Bonferroni corrected comparisons revealed that theta power at load 2 was significantly higher compared to load 4 ($p < 0.001$) and load 5 ($p = 0.002$), and that theta power at load 3 was significantly higher than at load 4 ($p = 0.010$). No other significant differences were observed. **(b)** The Variable Environment Group (VEG) obtained significantly lower theta power compared to the Fixed Environment Group (FEG) ($p = 0.045$). **(c)** Participants significantly decreased their theta band power from the pre-training (PRE) to the post-training measurement (POST) ($p < 0.001$). **(d)** Bonferroni corrected comparisons revealed that participants were able to significantly decrease their theta power at load 2 ($p < 0.001$), load 3 ($p < 0.001$), load 4 ($p < 0.001$) and load 5 ($p < 0.001$). The bars on the left side of each pair represent the pre-training measurement. Hatched bars on the right side - post-

training measurement. **(e)** Bonferroni corrected comparisons revealed that while there was no significant difference between groups in the pre-training measurement ($p = 0.686$), VEG had significantly lower theta power in comparison to FEG in the post-training measurement ($p = 0.004$). The blue bars on the left side of each pair represent VEG, and the orange ones represent FEG.

3.3. Telemetric Data

First, total time spent in the game and the mean number of matches played by each participant were calculated. Although there were no significant differences between the groups in the time spent playing SC2 ($p = 0.513$), participants from the Variable Environment Group were able to play [VEG: Mean = 99.46, SD = 25.09; FEG: Mean = 84.11, SD = 16.17; $t(41) = -2.311$, $p = 0.026$] and won significantly more matches [VEG: Mean = 60.75 SD = 16.794; FEG: Mean = 49.32, SD = 9.995; $t(41) = -2.619$, $p = 0.012$] in that time period, which corresponds to significant differences between the length of played matches in the tested groups [VEG: Mean = 1533.05, SD = 383.31; FEG: Mean = 1780.25, SD = 353.71; $t(41) = 2.172$, $p = 0.036$].

Next, we focused on potential between-group differences based on variables indicated by the logistic regression models. T-tests revealed that participants from the VEG had a significantly higher PAC latency (VEG: Mean = 2.27, SD = 0.36; FEG: Mean = 2.02, SD = 0.35), $t(41) = -2.324$, $p = 0.025$, and a lower time of first army unit creation (VEG: Mean = 155.03, SD = 31.97; FEG: Mean = 192.13, SD = 43.24), $t(38) = 3.121$, $p = 0.003$. No significant between-group differences in unit variability ($p = 0.117$), first supply event time ($p = 0.851$), or extracting-spending minerals ratio ($p = 0.093$) were found.

All results are presented in Figure 6.

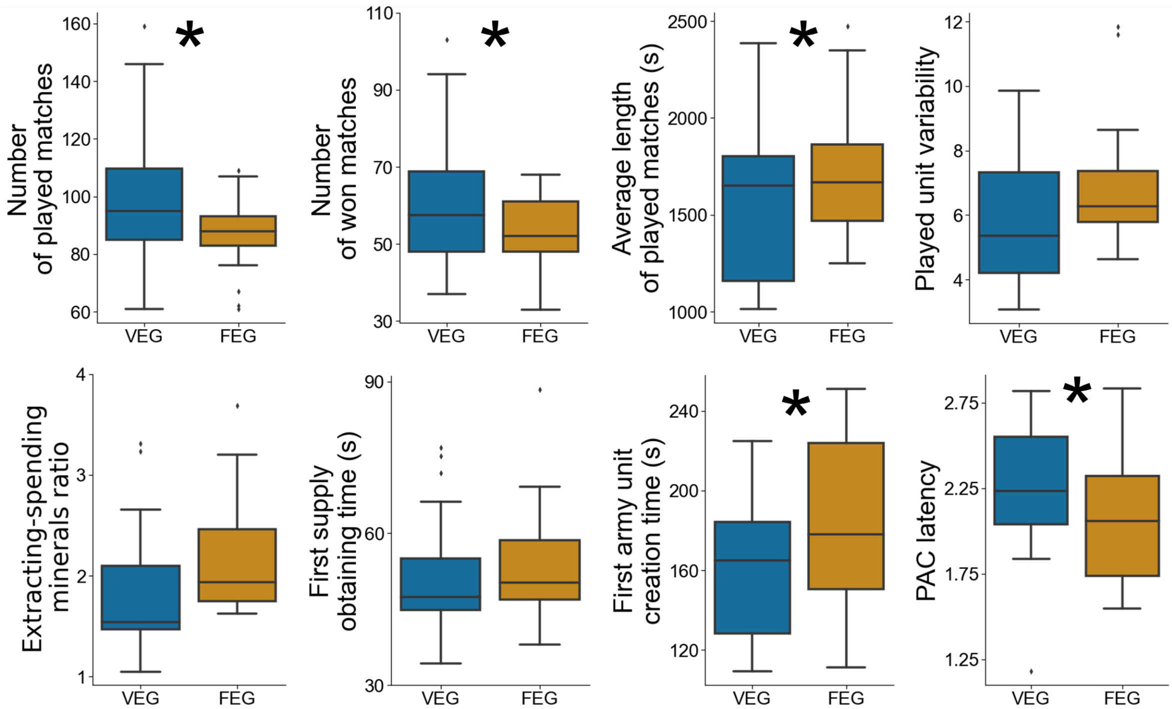

FIGURE 6 | The group comparison is presented on 8 telemetric variables, which were selected using logistic regression. The Variable Environment Group (VEG) was able to achieve significantly better in-game performance based on 5 of the presented variables than the Fixed Environment Group (FEG). Asterisks indicate significant differences ($p < 0.05$).

Importantly, all variables except for PAC latency indicate better VEG performance. Higher PAC latency may be due to greater game diversity in the VEG, which can be associated with longer information processing and decision-making times.

3.4. Psychophysiological, behavioral, and telemetric data

3.4.1. Predictive character of behavioral data

First, we created linear regression models containing a mean (averaged across all loads) K value obtained from pre-training measurement as a predictor, group as a moderator variable, and consecutive telemetric variables selected by the logistic regression model as a dependent variables.

The prepared models were successful in predicting only PAC latency [$F(3, 39) = 7.243$, $p < 0.001$, $R^2 = 0.308$], showing a significant constant value ($\beta = 1.628$, $p < 0.001$), group ($\beta = 2.3396$, $p < 0.001$), and an interaction between mean K value and group ($\beta = -0.954$, $p < 0.001$).

Additional analyses revealed that average K value from the pre-training measurement was a significant predictor for the VEG ($\beta = -0.737$, $p < 0.001$) but not for the FEG ($\beta = 0.217$, $p = 0.072$).

The relationship between initial, average K value and PAC latency is presented in Figure 7.

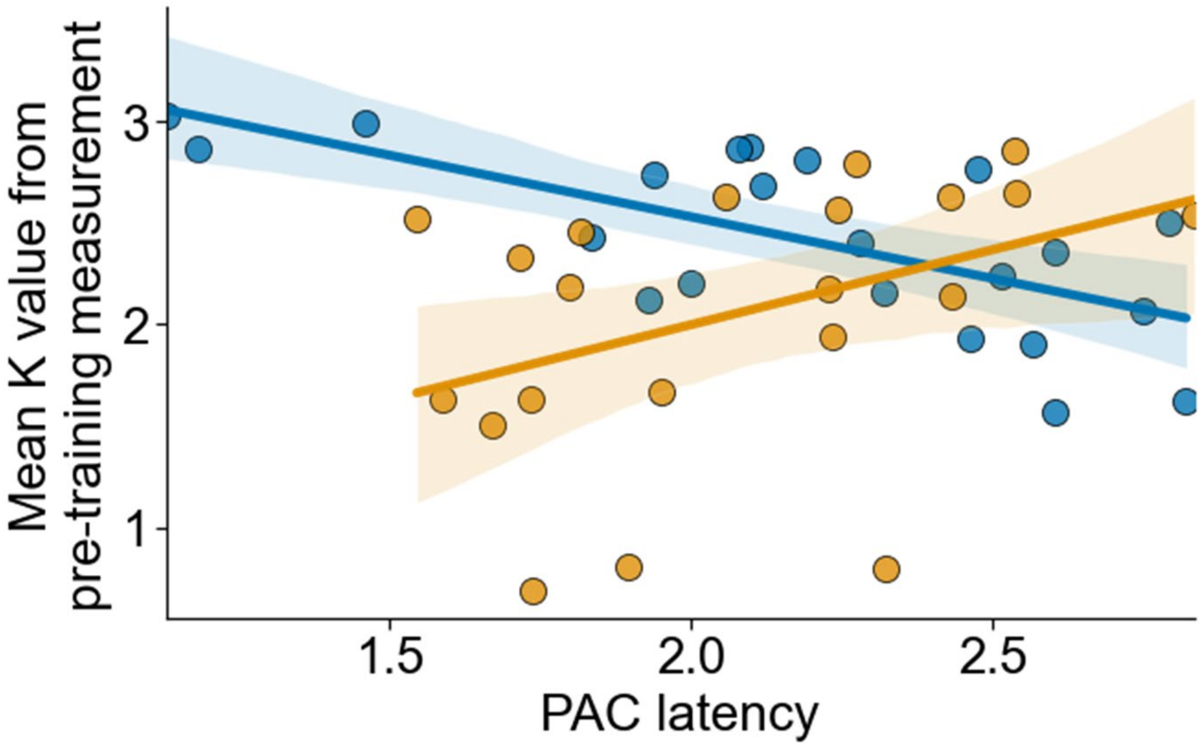

FIGURE 7 | Scatterplots showing the relationship between the average K value from pre-training measurement and PAC latency. Blue markers refer to VEG and orange ones refer to FEG. The scatterplot presents only significant linear regression models with the behavioral indicator (K) as a predictor.

To better understand the relationship between K value and proficiency gained through the training, we repeated analyses presented in the previous part. Linear regression model with average K value from the pre-training measurement as a predictor, group as a moderator variable, and the difference in individual level of proficiency (in-game achievements obtained from the last 10 matches - first 10 matches) as a dependent variables turn out to be insignificant. K-value was not predictive for proficiency gained through the training.

3.4.2. Predictive character of alpha band power

Linear regression models containing mean (averaged across all loads) alpha-band power obtained from pre-training measurement as a predictor, group as a moderator variable, and consecutive telemetry variables selected by logistic regression as dependent variables were created.

The prepared models were successful in predicting: (1) average length of played matches [$F(3, 39) = 9.453$, $p < 0.001$, $R^2 = 0.421$]; (2) number of won matches [$F(3, 39) = 10.29$, $p < 0.001$, $R^2 = 0.399$]; (3) number of played matches [$F(3, 39) = 10.36$, $p < 0.001$, $R^2 = 0.401$]; and (4) player's units variability [$F(3, 39) = 4.099$, $p = 0.012$, $R^2 = 0.181$]. The remaining models were non-significant: (1) player's first supply collection time [$F(3, 39) = 0.4926$, $p = 0.670$, $R^2 = -0.038$]; (2) player's first army unit creation time [$F(3, 39) = 1.615$, $p = 0.202$, $R^2 = 0.042$]; (3) extracting-spending minerals ratio [$F(3, 39) = 2.259$, $p = 0.097$, $R^2 = 0.083$]; (4) player's average PAC latency [$F(3, 39) = 2.086$, $p = 0.118$, $R^2 = 0.072$]. The exact results presenting initial alpha power and the influence of the constant are presented in Table 4.

As all the prepared models contained significant interaction effects, we decided to check the influence of theta initial power across groups.

While there was a significant, negative relationship between initial alpha and (1) average length of played matches [$\beta = -220.33$, $p < 0.001$)] and (2) player's units variability [$\beta = -0.758$, $p = 0.009$], and positive relationships between initial alpha and (1) number of played matches [$\beta = 13.022$ $p < 0.001$] and (2) number of won matches [$\beta = 8.143$, $p < 0.001$] in the VEG, in the FEG only negative relationships between (1) number of played matches [$\beta = 3.733$ $p = 0.049$] and (2) number of matches won [$\beta = 2.839$, $p = 0.027$] remained significant.

To better understand the relationship between initial alpha power and proficiency gained through the training, we repeated analyses presented in the previous part. Linear regression model contained average alpha power from the pre-training measurement as a predictor, group as a moderator variable, and the difference in individual level of proficiency (in-game achievements obtained from the last 10 matches - first 10 matches) as a dependent variables.

Initial alpha power turned out to be successful in predicting (1) changes in the average length of played matches [$F(3, 39) = 4.981$, $p = 0.005$, $R^2 = 0.234$], (2) changes in the variability of played units [$F(3, 39) = 6.458$, $p = 0.001$, $R^2 = 0.296$], (3) changes in player's first supply collection time [$F(3, 39) = 4.399$, $p = 0.014$, $R^2 = 0.204$] and (4) changes in player's first army unit creation time [$F(3, 39) = 5.158$, $p = 0.005$, $R^2 = 0.242$]. As we based on the difference between last and first 10 matches, we excluded the number of played and won matches from this part of analyses. The remaining models were non-significant.

As two of the prepared models contained significant interaction effects, we decided to check the influence of alpha initial power across groups.

While there was a significant, negative relationship between initial alpha and (1) changes in the average length of played matches [$\beta = -177.17$, $p = 0.005$)] and (2) changes in player's units variability [$\beta = -0.752$, $p = 0.05$] in the VEG, in the FEG only positive relationships between changes in player's units variability [$\beta = 6.02$, $p = 0.047$] remained significant.

Scatterplots showing relationships between initial alpha power and telemetric variables are presented in Figure 8.

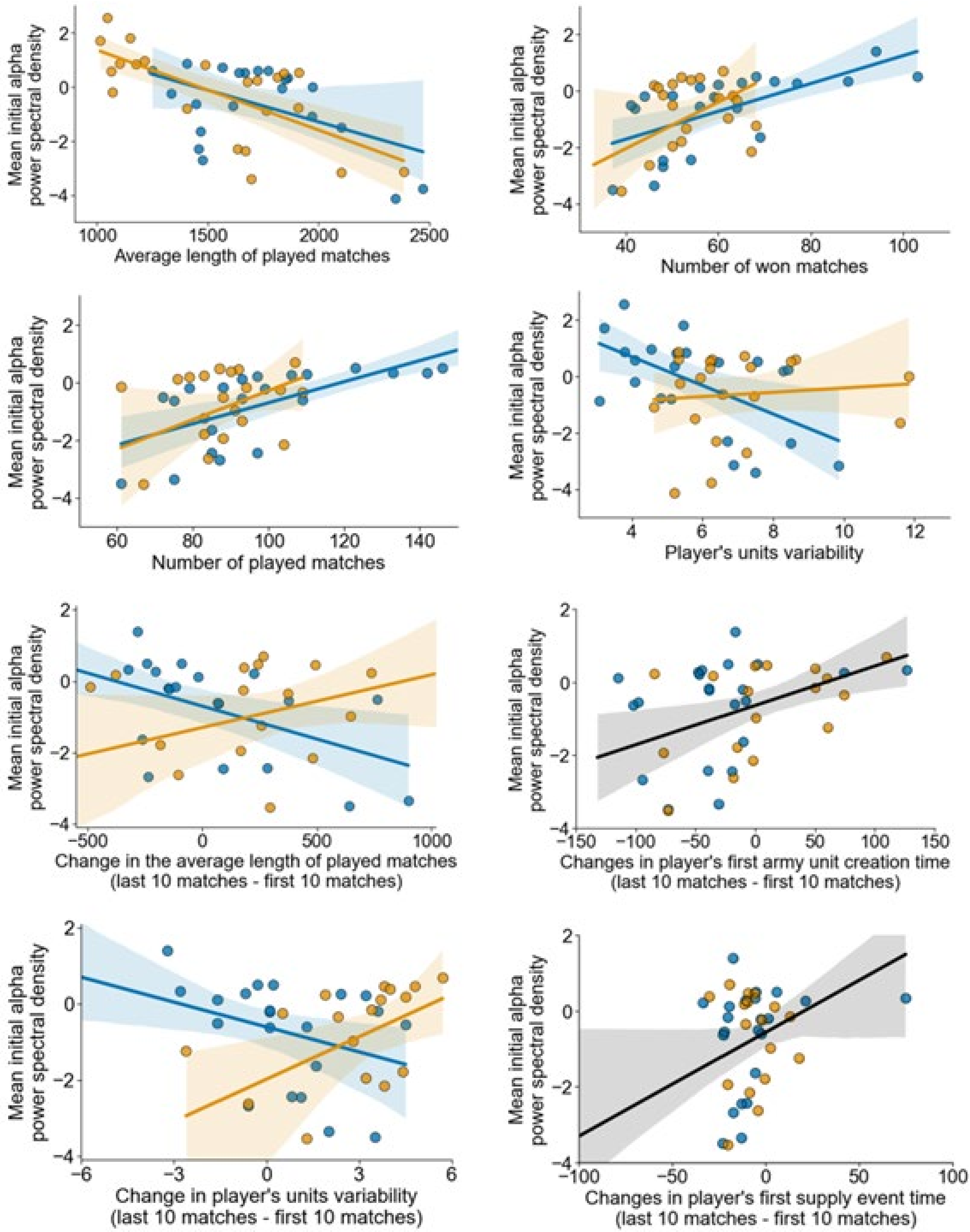

FIGURE 8 | Scatterplots showing the relationship between the initial alpha power and the selected telemetric variables. Blue markers refer to VEG and orange markers refer to FEG.

3.4.3. Predictive character of theta band power

Similar linear regression models containing mean (averaged across all loads) theta-band power obtained from pre-training measurement as a predictor, group as a moderator variable, and consecutive telemetry variables as dependent variables were created.

The prepared models were successful in predicting: (1) average length of played matches [$F(3, 39) = 10.68$, $p < 0.001$, $R^2 = 0.409$]; (2) number of won matches [$F(3, 39) = 12.91$, $p < 0.001$, $R^2 = 0.46$]; (3) number of played matches [$F(3, 39) = 124.19$, $p < 0.001$, $R^2 = 0.624$]; (4) player's units variability [$F(3, 39) = 7.958$, $p < 0.001$, $R^2 = 0.332$]; and (5) extracting-spending minerals ratio [$F(3, 39) = 5.653$, $p = 0.002$, $R^2 = 0.25$]. The remaining models were non-significant: (1) player's first supply collection time [$F(3, 39) = 0.951$, $p = 0.426$, $R^2 = -0.003$]; (2) player's first army unit creation time [$F(3, 39) = 1.584$, $p = 0.209$, $R^2 = 0.04$]; and (3) player's average PAC latency [$F(3, 39) = 1.302$, $p = 0.288$, $R^2 = 0.021$]. The exact results presenting the initial alpha power and the constant's influence are presented in Table 5.

As two models contained a significant interaction effect, we decided to check the influence of theta initial power across groups. All of the prepared additional models turned out to be significant in both groups [VEG: (1) Number of won matches: $\beta = -20.640$, $p < 0.001$; (2) Number of played matches: $\beta = -33.368$, $p < 0.001$; FEG: (1) Number of won matches: $\beta = -6.897$, $p = 0.027$; (2) Number of matches played: $\beta = --15.308$, $p < 0.001$].

To better understand the relationship between initial theta power and proficiency gained through the training, we repeated analyses presented in the previous part. Linear regression model contained average theta power from the pre-training measurement as a predictor, group as a moderator variable, and the difference in individual level of proficiency (in-game achievements obtained from the last 10 matches - first 10 matches) as a dependent variables.

Initial theta power turned out to be successful only in predicting changes in the average length of played matches [$F(3, 39) = 4.886$, $p = 0.006$, $R^2 = 0.230$]. As we based on the difference between last and first 10 matches, we excluded the number of played and won matches from this part of analyses. The remaining models were non-significant.

The exact results presenting initial alpha power and the influence of the constant are presented in Table 4.

As the prepared model contained significant interaction effects, we checked the influence of theta initial power across groups. Analyses revealed that the significant relationship between initial theta and changes in the average length of played matches was significant in VEG [$\beta = 508.6$, $p = 0.008$], but not in FEG [$\beta = -273.0$, $p = 0.086$].

Scatterplots showing relationships between initial theta power and telemetric variables are presented in Figure 9.

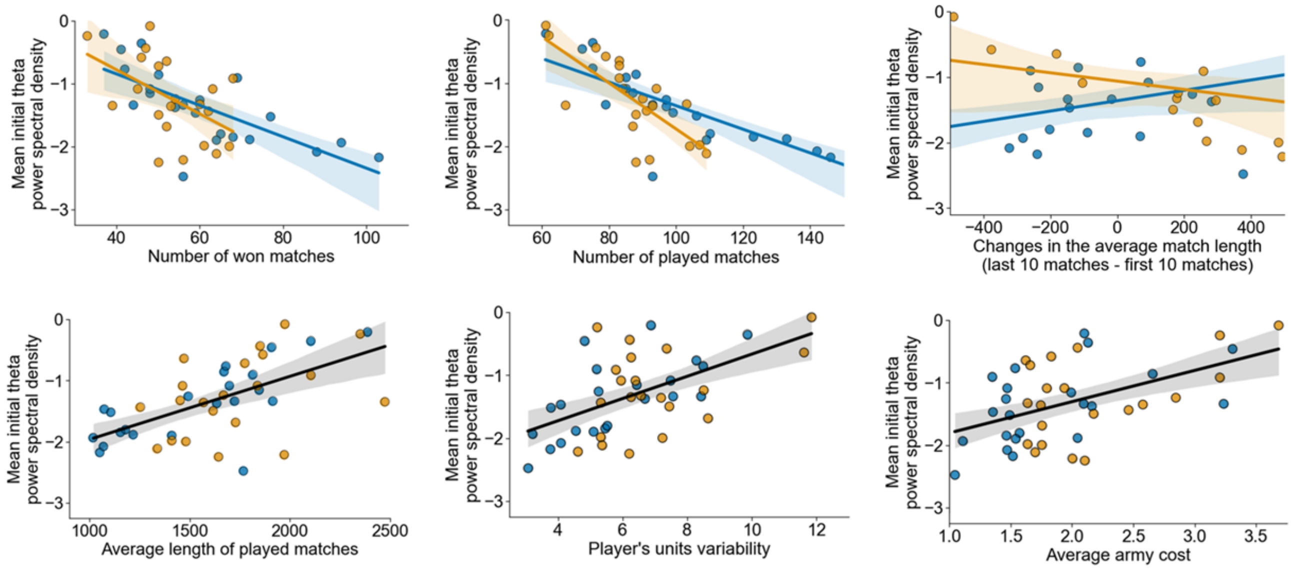

FIGURE 9 | Scatterplots showing the relationship between the initial theta power and selected telemetric variables. Blue markers refer to VEG and orange markers refer to FEG.

4. Discussion

The purpose of the current study was to investigate the relationship between the proficiency in RTS video games acquired during training and the VWM capacity indexed by EEG oscillations. To achieve this, we recruited participants who had no experience with playing RTS, FPS and TPS gamers and asked them to play SC2 for 30 hours. Participants were divided into two groups, with two independent training models that differed in terms of the number of potential opponents and strategies they could use. While one of the applied training regimens (VEG) should effectively simulate the complex entertainment that the game itself enables, the other (FEG) could be compared to a stable cognitive training in a slightly more entertaining form guaranteed by use of a video game. This allowed us – at least partially – to replicate the actual conditions in which players find themselves while playing video games in normal life, compared to more typical laboratory conditions (Baniqued et al., 2013; Smith et al., 2020)

Participants underwent EEG measurements before and after the training, during which they completed a change detection task – one of the most common tasks used to measure the capacity of VWM. In this way, we were able to identify the alpha and theta power of our participants from individual measurements, which can be interpreted as neurophysiological indicators of VWM.

In the second step, we extracted the telemetric variables from each of the matches played by our participants during the training. To avoid analyzing all of the telemetric components, we pre-selected them, focusing only on those that were not related to the opponent's results, strategy, and map type. Due to the subsequent use of logistic regression, we selected 8 telemetric variables that seemed to have the most predictive character in the case of winning a single match, which is the main variable that reflects player skill. Furthermore, it allowed us to avoid focusing on the level of difficulty – which varied during training, depending on the player's proficiency – and gave us variables that could potentially be applied to players with different levels of advancement.

Analysis of the behavioral and EEG data revealed the presence of all main effects, indicating that the procedure was correctly performed and that alpha and theta log power spectral densities were accurately calculated. Both bands turned out to be sensitive to the number of elements that participants needed to store in memory (loads) and changed linearly with the memory load. It is important to mention that whereas some studies found a decrease in theta and alpha power with decreasing load, the opposite pattern is more frequently reported (Brzezicka et al., 2019; Steiger et al., 2019; Fernández et al., 2021). The inconsistency of these results may be caused by consistent theta and alpha changes, which may indicate the avoidance of states such as boredom and overload during the task or the training (Katahira et al., 2018). Participants from both groups in our study were also able to significantly increase their alpha and decrease theta log power spectral densities from the pre- to post-training measurements, which is in line with studies showing that such effects can be related to better cognitive and memory performance in particular (Brzezicka et al., 2019; Hu et al., 2019; Wianda and Ross, 2019; Kardan et al., 2020).

Then should be also emphasized that the alpha and theta patterns in our study differ from each other, which - combined with inconsistent literature - make them hard to compare and interpret. Although both of the mentioned oscillations can successfully represent the level of WM load, they are usually linked with other mechanisms (Riddle et al., 2020). Frontal theta is commonly thought to play a key role in determining WM capacity (Wolinski et al., 2018), while posterior alpha is more often referred to as an indicator of the active stage of visual processing (Wianda and Ross, 2019). Our results indicate that posterior alpha is a stronger predictor of in-game achievements (it successfully predicted averaged in-game indicators and changes in game proficiency gained over the training), which may be related to its role in visual processing. Oscillations, unlike event-related potentials such as CDA, are also rarely directly associated with behavioral outcomes, assuming that they are more sensitive and accurate measures of the processes behind a given cognitive skill. Therefore future research should focus on replication, which may allow for better understanding the results by combining and/or comparing different types of VWM indices. What is more, it is possible that different methods of calculating alpha and theta power could lead to greater consistency across literature and giving a more in-depth understanding thanks to different analytical approaches.

Analysis of the telemetric data showed statistically significant differences between groups on five of the tested indicators. Participants from the VEG were able to play and win significantly more matches in the same period of time in comparison to the FEG. It is the result of playing significantly shorter matches, which is in line with one of the most basic rules of SC2 players, stating that you can either lose the match for a long time or win it quickly. Further, VEG players were able to create attacking units significantly faster in comparison to FEG players. All of those variables indicate further advancement in the game environment in the VEG.

Interestingly, one exception is that the VEG participants needed a significantly longer time to perform actions in a new PAC (measured by PAC latency). This advantage for the FEG may be associated with lower variation in the opponent's behavior, which was largely repetitive and did not require as careful analysis of subsequent movements as in the VEG.

The applied training models differed in the level of complexity, but not in the basic level of difficulty, which changed during the training along with the players' skills. Nevertheless, VEG was able to achieve higher in-game performance compared to FEG. It may be related to the structure of training itself, which in VEG was more engaging and stimulating for players. It is possible that it helped participants to maintain a higher level of motivation. What is more, VEG was forced to better understand the game structure, models, and to master more specific game strategies in order to win the match. Then it is worth noting that only this model, at least to a small extent, reflects the actual game environment and possibilities, which make SC2 popular among players.

It should be emphasised then that there is no single variable behind the result of a particular match or the level of a player's advancement. In the SC2 environment, we can distinguish dozens of highly correlated variables, which – analysed together, separately, or in specific clusters – may reflect the player's skills presented in the match. This leads to the inevitability of observing similar relationships in different types of variables. Given that, we decided to present a set of selected variables anyway. We wanted to present a wider spectrum of the same phenomenon, proving at the same time that it is not a random result of correlating a large number of variables.

The most essential part of the current study concerns potential predictive models that, thanks to the initial behavioral and neurophysiological indicators, could predict the level of proficiency that our participants achieved during training.

The initial, average K value proved to be effective in predicting PAC latency only. Interestingly, that is the only telemetric variable which showed an advantage for the FEG. Regardless, the model turned out to be significant only for the VEG and indicates that those players with a higher initial K value had shorter PAC latency, thereby also distinguishing those VEG players who were able to perform better in that field.

Both (pre-training) initial alpha and initial theta log-power spectral densities were able to correctly explain the value of 4 (in case of alpha) and 5 (in case of theta) of the tested telemetric variables.

Interestingly, most of the prepared models contained a predictor group (initial alpha or initial theta) × group (VEG *vs* FEG) interaction, showing a stronger, significant effect in the VEG. This may show that FEG participants, despite having similar individual potential, did not have the opportunity to develop adequately in an unfavourable, monotonous environment. Importantly, all the observed trends of the predictor (initial alpha and theta) influence seem to be in line with observed between-measurements changes. The higher level of the initial alpha power, and the lower level in the case of initial theta power, turned out to be associated with achieving greater in-game results. After the training intervention, we see adequate changes in the form of an overall increase in alpha power and a decrease in theta power. All of the obtained results reflect the relationship between VWM and SC2 training.

The obtained results also confirmed our expectation regarding the influence of the applied training model. The presented results may indicate that the natural predispositions of a player can result in better in-game development only in a favourable environment. More importantly, these results may explain the divergence in studies using video games, which investigate their influence on neurophysiological and behavioral indicators of human cognitive ability. While recent studies accurately describe the type and duration of applied video game training, the exact type of training (with detailed parameters used to define the game environment) is rarely explained. It turns out that not only the type of game or play time but also the way of playing has a key impact on the relationship between human cognitive ability (such as visual working memory) and actual in-game behavior. This aspect can be crucial not only in trying to explain the potential impact of video games on human behavior but also in extending the obtained results to a group of professional players.

Therefore, the results seem to be promising for advanced or even professional players looking to improve their in-game performance. Assuming that the relationship between video games and selected cognitive functions is two-sided, it is possible that adequate training, focusing on cognitive functions related to in-game performance, could improve player outcomes. From this perspective our results are of a potential interest for the esports community, pointing to the possibility of an alternative way of enhancing their abilities.

The playing of commercial video games and inspection of respective neural associations is a relatively novel research domain with a promising future. Nevertheless, this also implies a lack of the necessary findings to establish the outline of this domain. For this reason, we believe that this study could guide research in future studies.

Therefore, it is important to mention that future investigations should examine a wider range of carefully selected tasks, which can contribute to creating a more complete spectrum of cognitive functions and the changes that they undergo through video game training. Moreover, using more advanced statistical analyses, like hierarchical linear models, could help to increase our knowledge of the relationship between EEG indicators and behavioral variables, both from the cognitive paradigms themselves and from more complex game environments. It is also possible that players may differ in their preferred factions (Terran, Protoss, Zerg) and their capabilities and thus achieve different (potentially better) results in training by playing them. Future research may want to check the differences in training obtained due to the implemented factions or even examine players' preferences in that term by combining it with behavioral or personality traits. What is more, the use of other machine learning methods to better select significant telemetric variables, reflecting player behavior or the strategies they adopt, may also allow for presentation of a broader picture of the discussed relationships.

The lack of a sufficient control group and a small sample of active groups are also an unquestionable limitation. It should be emphasised that this limitation is largely due to drop-out, which is a common problem in longitudinal studies. Further, our results are based solely on RTS training which, according to other studies, may require different cognitive functions and influence players differently when compared to FPS or TPS games. To be able to clearly understand the obtained results, they should also be compared to data and models built on professional - or at least more advanced - video game players from different types of video games.

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Ethics Statement

The studies involving human participants were reviewed and approved by Komisja ds. Etyki Badań Naukowych Wydziału Psychologii w Warszawie (Ethics committee of the Department of Psychology at University of Social Sciences and Humanities). The participants provided written informed consent to participate in this study.

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Conflict of Interest Statement

The authors declare that the research was conducted in the absence of any commercial or financial relationship that could be construed as a potential conflict of interest.

Data availability statement

The datasets generated and/or analysed during the current study are available from the corresponding author on reasonable request.

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TABLE 1. | Specific K values obtained from both measurements.

	Pre-training measurement		Post-training measurement	
	FEG	**VEG**	**FEG**	**VEG**
Load 2	M = 1.679, SD = 0.262	M = 1.746, SD = 0.181	M = 1.741, SD = 0.271	M = 1.850, SD = 0.134
Load 3	M = 2.087, SD = 0.554	M = 2.309, SD = 0.418	M = 2.243, SD = 0.427	M = 2.557, SD = 0.337
Load 4	M = 2.195, SD = 0.860	M = 2.691, SD = 0.517	M = 2.481, SD = 0.724	M = 3.069, SD = 0.503
Load 5	M = 2.266, SD = 1.208	M = 2.916, SD = 0.765	M = 2.622, SD = 0.974	M = 3.272, SD = 0.739
Mean	M = 2.054, SD = 0.673	M = 2.416, SD = 0.435	M = 2.272, SD = 0.559	M = 2.687, SD = 0.392

TABLE 2. | Specific values of the alpha power obtained from both measurements.

	Pre-training measurement		Post-training measurement	
	FEG	**VEG**	**FEG**	**VEG**
Load 2	M = -1.050, SD = 1.554	M = -0.762, SD = 1.408	M = -0.730, SD = 1.618	M = -0.339, SD = 1.642
Load 3	M = -1.067, SD = 1.673	M = -0.730, SD = 1.393	M = -0.634, SD = 1.519	M = -0.252, SD = 1.802
Load 4	M = -0.9132, SD = 1.578	M = -0.644, SD = 1.337	M = -0.633, SD = 1.477	M = -0.132, SD = 1.681
Load 5	M = -0.760, SD = 1.505	M = -0.584, SD = 1.389	M = -0.602, SD = 1.424,	M = -0.201, SD = 1.703
Mean	M = -0.947, SD = 1.541	M = -0.680, SD = 1.369	M = -0.650, SD = 1.501	M = -0.231, SD = 1.692

TABLE 3. | Specific values of theta power obtained from both measurements.

	Pre-training measurement		Post-training measurement	
	FEG	**VEG**	**FEG**	**VEG**
Load 2	M = -1.133, SD = 0.559	M = -1.317, SD = 0.598	M = -1.602, SD = 0.855	M = -2.315, SD = 0.683
Load 3	M = -1.306, SD = 0.597	M = -1.336, SD = 0.557	M = -1.529, SD = 0.784	M = -2.352, SD = 0.693
Load 4	M = -1.320, SD = 0.650	M = -1.384, M = 0.705	M = -1.743, SD = 1.047	M = -2.433, SD = 0.708
Load 5	M = -1.424, SD = 0.631	M = -1.442, SD = 0.640	M = -1.562, SD = 0.902	M = -2.328, SD = 0.743
Mean	M = -1.295, SD = 0.590	M = -1.370, SD = 0.612	M = -1.609, SD = 0.889	M = -2.357, SD = 0.695

TABLE 4. | Regression tables obtained for linear regression models with alpha power as a predictor. Results were calculated for all participants (without division into groups).

Initial alpha's power predictive impact on selected telemetric variables

Dependent variable	Model variables	β	*p*
Average length of played matches	**Constant**	***1650.34***	***p* < 0.001***
	Initial alpha	*-79.77*	*p* = 0.056
	Group	***-260.96***	***p* = 0.011***
	Interaction	***-140.56***	***p* = 0.025***
Number of won matches	**Constant**	**50.022**	***p* < 0.001***
	Initial alpha	2.839	*p* = 0.096
	Group	**10.470**	***p* = 0.013***
	Interaction	**5.305**	***p* = 0.039***
Number of played matches	**Constant**	**90.393**	***p* < 0.001***
	Initial alpha	3.733	*p* = 0.005
	Group	**19.098**	***p* = 0.002***
	Interaction	**3.490**	***p* = 0.011***
Player's units variability	**Constant**	**7.016**	***p* < 0.001***
	Initial alpha	0.106	*p* = 0.689
	Group	**-1.713**	***p* = 0.010***
	Interaction	**-0.863**	***p* = 0.032***
Change in the average length of played matches	**Constant**	**304.83**	***p* = 0.006***
	Initial alpha	99.35	*p* = 0.689

(last 10 matches – first 10 matches)	**Group**	**-434.79**	***p* = 0.003***
	Interaction	**-276.51**	***p* = 0.018***
Change in player's units variability (last 10 matches – first 10 matches)	Constant	-2.280	*p* = 0.719
	Initial alpha	**10.997**	***p* = 0.002***
	Group	-1.528	*p* = 0.855
	Interaction	-6.855	*p* = 0.172
Change in player's first supply collection time (last 10 matches – first 10 matches)	**Constant**	**7.016**	***p* < 0.001***
	Initial alpha	0.106	*p* = 0.689
	Group	**-1.713**	***p* = 0.010***
	Interaction	**-0.863**	***p* = 0.032***
Change in player's first army unit creation time (last 10 matches – first 10 matches)	Constant	22.925	*p* = 0.119
	Initial alpha	**24.657**	***p* = 0.003***
	Group	**-45.797**	***p* = 0.021***
	Interaction	-13.520	*p* = 0.235

TABLE 5. | Regression tables obtained for linear regression models with theta's log power spectral density as a predictor. Results were calculated for all participants (without division into groups).

Initial theta's power predictive impact on selected telemetric variables			
Dependent variable	Model variables	β	*p*
Average length of played matches	**Constant**	***1988.67***	***p* < 0.001***
	Initial theta	***210.60***	***p* = 0.037***
	Group	*204.04*	*p* = 0.320
	Interaction	*266.40*	*p* = 0.064
Number of won matches	**Constant**	**44.728**	***p* < 0.001***
	Initial theta	-6.897	*p* = 0.068
	Group	-12.051	*p* = 0.0123
	Interaction	**-13.743**	***p* = 0.013***
Number of played matches	**Constant**	**67.757**	***p* < 0.001***
	Initial theta	**-15.308**	***p* = 0.002***
	Group	-18.835	*p* = 0.186
	Interaction	**-18.060**	***p* = 0.009***
Player's units variability	**Constant**	**8.455**	***p* < 0.001***
	Initial theta	**1.234**	***p* = 0.033***
	Group	0.294	*p* = 0.801
	Interaction	0.906	*p* = 0.264
Extracting-spending minerals ratio	**Costant**	**2.702**	***p* < 0.001***
	Initial theta	**0.435**	***p* = 0.026***
	Group	-0.159	*p* = 0.686

	Interaction	-0.019	*p* = 0.737
Change in the average length of played matches (last 10 matches – first 10 matches)	Constant	-120.2	*p* = 0.534
	Initial theta	-273.0	*p* = 0.061
	Group	**628.9**	***p* = 0.030***
	Interaction	**651.2**	***p* = 0.002***

Supplementary Material

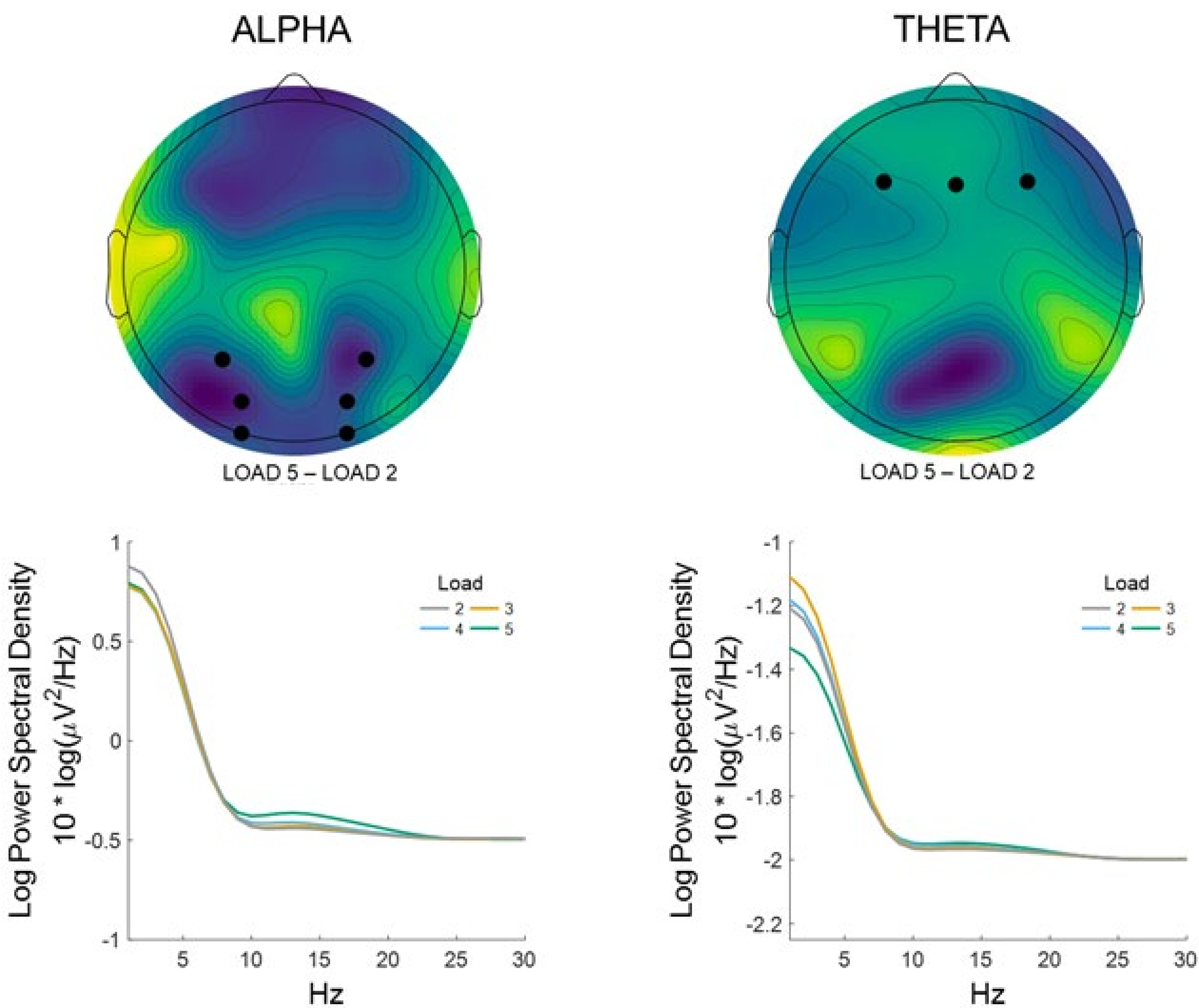
1.1 Supplementary Tables

Supplementary Table 1 | Number of removed EEG epochs per condition.

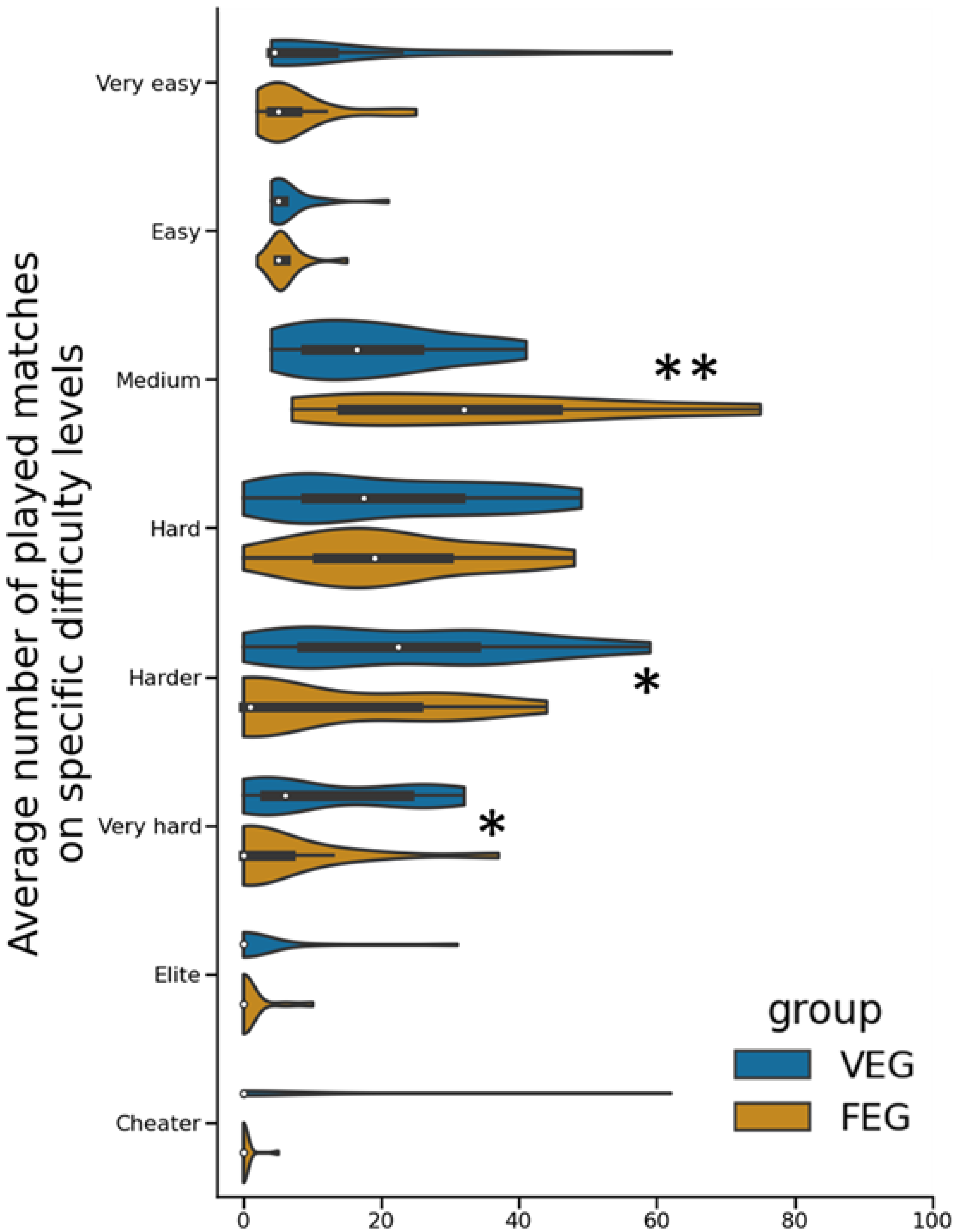
	PRE-TRAINING		POST-TRAINING	
	VEG	**FEG**	**VEG**	**FEG**
Average number of epochs removed as a result of incorrect response				
Load 2	17.36 (± 6.43)	19.78 (± 10.64)	15.13 (± 10.09)	18.78 (± 14.28)
Load 3	27.77 (± 9.72)	33.01 (± 13.02)	20.95 (± 10.14)	28.58 (± 12.45)
Load 4	36.23 (± 9.35)	43.28 (± 12.93)	30.27 (± 11.31)	37.89 (± 12.99)
Load 5	41.41 (± 9.72)	51.89 (± 13.06)	38.91 (± 9.75)	44.95 (± 11.12)
Average number of epochs removed as a result of bad data quality				
Load 2	15.72 (± 6.94)	18.28 (± 10.33)	16.13 (± 11.07)	20.15 (± 12.14)
Load 3	13.77 (± 7.29)	20.06 (± 10.97)	13.45 (± 8.49)	17.36 (± 9.97)
Load 4	13.05 (± 6.42)	13.22 (± 8.92)	12.45 (± 8.71)	18.53 (± 10.19)
Load 5	13.86 (± 6.37)	13.89 (± 7.69)	13.77 (± 5.57)	18.58 (± 9.68)

All included EEG data remained with more than 50% of epochs per load. Presented numbers refer to participants included in the study.

1.2 Supplementary Figures

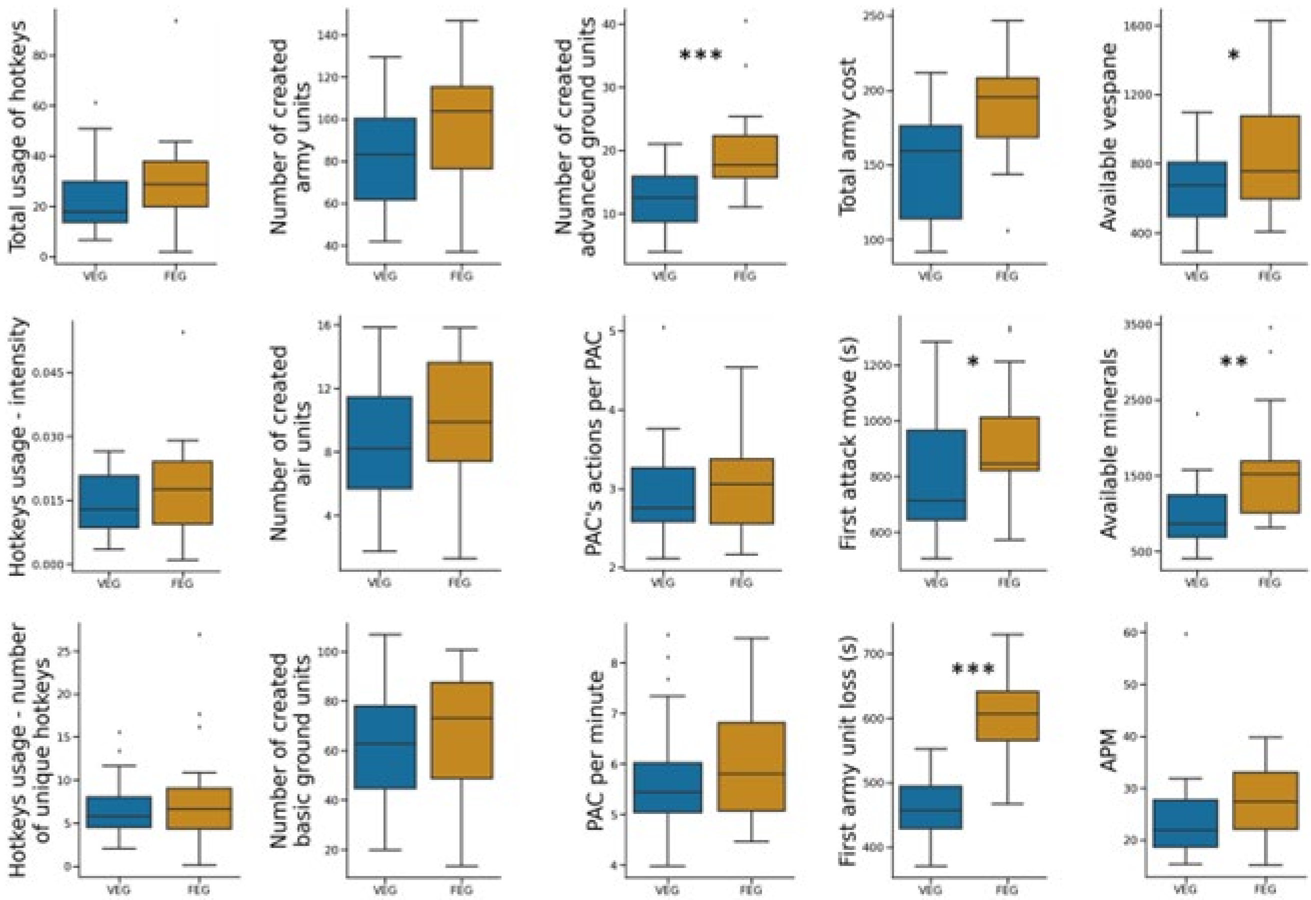


Supplementary Figure 1. Topographical maps and power spectrum for analyzed alpha and theta bands. Alpha power (8-12 Hz) was averaged across electrodes O1, O2, P3, P4, PO3 and PO4. Theta power (4-8 Hz) was averaged across electrodes F3, Fz and F4. Both power bands were obtained from 1 second after memory array presentation. Presented graphs were created based on all data obtained from both groups and measurements.

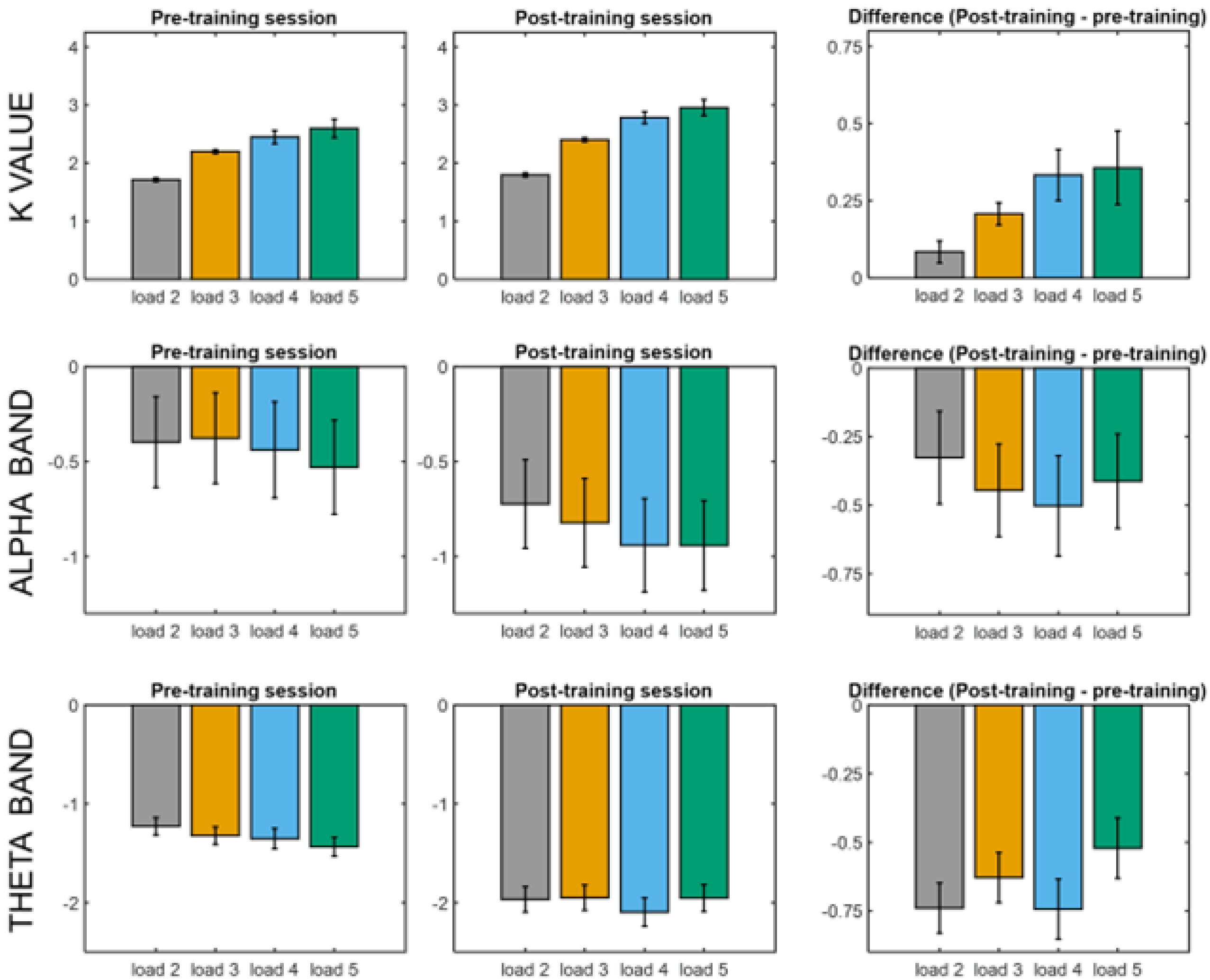


Supplementary Figure 2. Average number of played matches on specific difficulty levels. FEG played significantly more matches on medium level of difficulty (p = 0.006) in comparison to VEG. On the other hand, VEG played significantly more matches on harder (p

= 0.029) and very hard (p = 0.047) levels of difficulty. No other significant differences were observed. Asterisks indicate statistical significance: * p < 0.05, ** p < 0.01.



Supplementary Figure 3. Indicators of in-game achievements, which were later excluded from the study. Presented indicators are not directly related to the level of difficulty and none of them predicted the match result effectively. Asterisks indicate statistical significance between group differences: * p < 0.05, ** p < 0.01, *** p < 0.001.



Supplementary Figure 4. The average K-values, alpha power and theta power obtained from both groups from pre- and post-training measurements along witch observed changes.

Authors' contributions

Warszawa, 30.08.2022

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Przyczyniłam się do:

☐	Koncepcja badania, hipotezy	■	Przygotowanie grafik
☐	Planowanie badania, dobór metod badawczych	■	Interpretacja danych, wyciąganie wniosków
■	Przeprowadzenie badania, zebranie danych	■	Napisanie pracy
■	Wykonanie analiz statystycznych	■	Redagowanie kolejnych wersji pracy
■	Opracowanie danych behawioralnych	■	Odpowiedź na recenzje
■	Opracowanie danych EEG	■	Przegląd literatury

Swój wkład procentowy w powstanie publikacji szacuję na

87 **%.**

Jakubowska
Podpis

Warszawa, 30.08.2022

Alicja Anna Binkowska
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Tytuł pracy: Jakubowska N., Binkowska A.A., Arslan I.V., Chałatkiewicz I., Dąbkowska M., Podolecka W.M., Dobrowolski P., Brzezicka A. Video game proficiency predicted by EEG oscillatory indexes of visual working memory (artykuł w recenzji w Frontiers in psychology).

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☐	Wykonanie analiz statystycznych	■	Redagowanie kolejnych wersji pracy
☐	Opracowanie danych behawioralnych	☐	Odpowiedź na recenzje
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