



Research article

How is social dominance related to our short-term memory? An EEG/ERP investigation of encoding and retrieval during a working memory task

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ABSTRACT

Social hierarchies exist in all societies and impact cognitive functions, brain mechanisms, social interactions, and behaviors. High status individuals often exhibit enhanced working memory (WM) performance compared to lower status individuals. This study examined whether individual differences in social dominance, as a predictor of future status, relate to WM abilities. Five hundred and twenty-five students completed the Personality Research Form dominance subscale questionnaire. From this sample, students with the highest and lowest scores were invited to participate in the study. Sixty-four participants volunteered to take part and were subsequently categorized into high- and low-dominance groups based on their dominance subscale questionnaire (PRF_d) scores. They performed a Sternberg WM task with set sizes of 1, 4, or 7 letters while their EEG was recorded. Event-related potential (ERP) and power spectral analysis revealed significantly reduced P3b amplitude and higher event-related synchronization (ERS) of theta and beta during encoding and retrieval phases in the high-than low-dominance group. Despite these neural processing differences, behavioral performance was equivalent between groups, potentially reflecting comparable cognitive load demands of the task across dominance levels. Further, there were similar P3b patterns for each set-size within groups. These findings provide initial evidence that individual differences in social dominance trait correlate with WM functioning, as indexed by neural processing efficiency during WM performance.

1. Introduction

Social hierarchies are a natural aspect of many species' lives, including humans, and understanding one's relative rank within these

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hierarchies is crucial for navigating complex social environments [1]. Social organisms heavily rely on hierarchies to interact with one another, as these hierarchical structures provide order, clarify individual and group roles, and promote social cohesion. Moreover, social hierarchies can serve as a driving force behind various behaviors, motivating individuals to strive for higher positions among their peers [2,3]. In human societies, social rank can be attained through various factors, including socio-economic status (SES), power, and dominance, among others [4]. SES is typically measured by factors such as income, education, employment status, and information about an individual's living environment [1]. Power refers to having or perceiving control over resources or group members, and it is a dynamic contextual factor that varies across different situations [3,5,6]. Dominance, on the other hand, involves the motivation to acquire resources through force and intimidation and is characterized by stable individual differences that persist across various situations [4]. Dominance can predict power and is often assessed through questionnaires that measure the motivational tendency towards forceful and intimidating behavior [7,8]. In fact, dominance is considered a strong predictor of competence and is even more predictive of emerging as a leader in groups than intelligence [9].

Behavioral and neural studies have demonstrated the broad impact of SES on various behaviors and cognitive functions [10]. Higher SES is positively correlated with selective attention and executive functions, as evidenced by numerous studies [11]. Additionally, higher SES is associated with better performance in different types of memory tasks, including working memory (WM) [12–18].

Furthermore, temporary increases in the sense of power have been found to enhance performance in executive functions, such as updating, inhibition, planning, mental rotation, and attention across various tasks. Hadar et al. suggest that power might exert its influence on cognitive performance through its impact on WM [19]. Their study demonstrates that the induction of social power leads to improved WM performance. However, the effects of power induction are transient in nature. In contrast, traits (such as dominance) reflect a long-lasting motivational tendency [20]. Recent research by Da Cruz et al. reveals that high-dominance men, assessed using the Personality Research Form Dominance Subscale (PRF_d) questionnaire, exhibit faster response times in tasks related to memory, learning, and emotion recognition, but they indicate no significant differences in terms of accuracy [21]. Additionally, Chou et al. show that both dominant children and rats, identified through dominance questionnaire and competitive tasks, respectively, demonstrate better memory capabilities and these enhanced memory capabilities, in turn, contribute reciprocally to the achievement of higher social dominance status [22].

Collectively, these findings highlight the intricate relationship between power, dominance, and memory performance. As mentioned above, temporary power inductions can boost cognitive performance, including WM, while long-lasting dominance trait influences long-term memory. Based on these findings, it is plausible to assume that high-dominance humans may also exhibit enhanced WM. In fact, these studies along with others (see below) lead us to think social dominance might be related to WM.

To study this, we employed both behavioral and neural paradigms to explore the potential connection between dominance and WM. Specifically, in studying the electrophysiological correlates of WM, our focus was primarily on slow-wave ERP components as well as time-frequency features and power spectral densities (see supplementary). In WM ERP research, two subcomponents of the P300, namely P3a and P3b, have consistently emerged as indicators of higher cognitive abilities associated with selective attention (P3a) and WM (P3b) [23,24]. The P3b component is particularly relevant to tasks requiring active WM engagement [25] and reflects cognitive load, indicating the extent to which WM resources are utilized [26,27]. Furthermore, the P3b component can provide insights into the maintenance of background information [28]. Additionally, examining time-frequency dynamics, such as event-related spectral perturbations (ERSP), during memory tasks can provide valuable insights into the temporal and spectral characteristics of neural activity associated with encoding, maintenance, and retrieval processes.

In the context of memory, two main regions of the brain play a key role: the hippocampus and the prefrontal cortex (PFC). These two regions communicate via brain waves of different frequencies, specifically theta and beta waves throughout hippocampal-PFC pathway [29–32].

Theta waves (4–8 Hz) are observed during light sleep, wakefulness, and relaxation. They are also associated with creativity and they contribute to memory consolidation and associative learning [33,34]. In the context of memory, theta waves are involved in weakening incorrect associations and reinforcing correct ones. To do so, the hippocampus and PFC communicate via theta oscillations, guiding what the brain learns during memory processes [31]. More specifically, theta oscillations of mPFC synchronize with hippocampal theta waves during WM processing and if they get disrupted, animals cannot perform WM tasks [35].

Beta waves (12–30 Hz) are low-frequency oscillations associated with conscious cognitive processes. During a memory task that requires information to be held in WM for short periods, the brain uses beta waves to switch between different pieces of information. Thus, one can think of beta waves as a “brake” that can control when to express information held in WM and when to clear it out, allowing the brain to shift the attention to something else and modify behavior. Therefore, beta waves are involved in top-down information processing, such as setting goals, plans, strategies, and task rules and they act as a gate, controlling information flow in WM [29,30].

To investigate the neural correlates of the relationship between dominance and WM, we employed a multifaceted approach combining behavioral measures with EEG. Our focus was on examining slow-wave ERP components, time-frequency features, and power spectral densities. Previous research has shown that the P3b component of the ERP, reflecting WM load, is sensitive to cognitive demands [24,26]. Additionally, theta and beta oscillations have been implicated in various stages of WM processing, including encoding, maintenance, and retrieval, primarily within the frontal and parietal regions [36–43]. By examining these electrophysiological markers, we aimed to elucidate the neural mechanisms underlying the potential association between dominance and WM performance.

While prior research has linked social dominance to general cognitive abilities, the specific neurophysiological correlates of the dominance-WM relationship remain underexplored. By combining behavioral and EEG measures, our study offers a novel perspective

on this topic. Through a detailed analysis of ERP components and ERSPs, we sought to identify neural markers that differentiate individuals with high and low dominance levels in terms of their WM performance. This way we aim to contribute to the growing body of research on the interplay between social hierarchy, cognition, and neural functioning.

2. Methods and materials

2.1. Participants

In this preregistered study (http://aspredicted.org/MH6_WY3), a total of 525 university students completed the PRF_d survey via Google Forms. To mitigate the influence of confounding variables and ensure a homogeneous sample we adopted several measures. One such measure involved controlling heightened levels of anxiety and hemispheric lateralization, which previous research has indicated can affect performance in similar tasks such as visual WM, response inhibition, and overall reaction times [44–46]. To do so, those with very high anxiety trait (scores higher than 54 in the STAI questionnaire) as well as left-handed students were excluded using the Edinburgh Handedness Inventory (EHI). This resulted in a final sample of 492 participants. Based on their PRF_d scores, the highest scorers (starting from 16 to 10) and lowest scorers (starting from 1 to 7) were invited to participate in the study (Fig. 1).

Of the initial sample, 64 participants (33 in high-dominance group, 31 in low-dominance group, 34 females, and 30 males) agreed to take part in the experimental WM tasks (further details provided in the instruments section), during which their EEG signals were recorded. Among these participants, the mean STAI score was 40.67 (SD = 8.93), with a mean of 40.03 (SD = 8.90) for high-dominants and 41.64 (SD = 9.20) for low-dominants.

Although no formal sample size calculation was conducted, the number of participants invited was determined based on previous EEG/ERP literature that indicated the required sample size for stabilizing the P300 component, ensuring sufficient statistical power, and accounting for effect size estimates [47,48]. Previous studies have shown that approximately 20 target trials and 24 participants are needed to stabilize the P300 component [49]. Moreover, considering the large effect size observed in dominance-related ERPs using the same PRF_d questionnaire [21], the selected sample size was deemed appropriate for capturing meaningful findings in the present study.

Prior to participating in the study, all participants provided informed consent, and the study protocol was approved by the local bioethics committee, adhering to the ethical principles outlined in the Declaration of Helsinki for human research. The PRF_d questionnaire used in this study consists of scores ranging from 1 to 16 [50]. To ensure a comprehensive representation of individual differences, participants were divided into two groups based on the following criteria. Since no clear cut-off point in the relevant

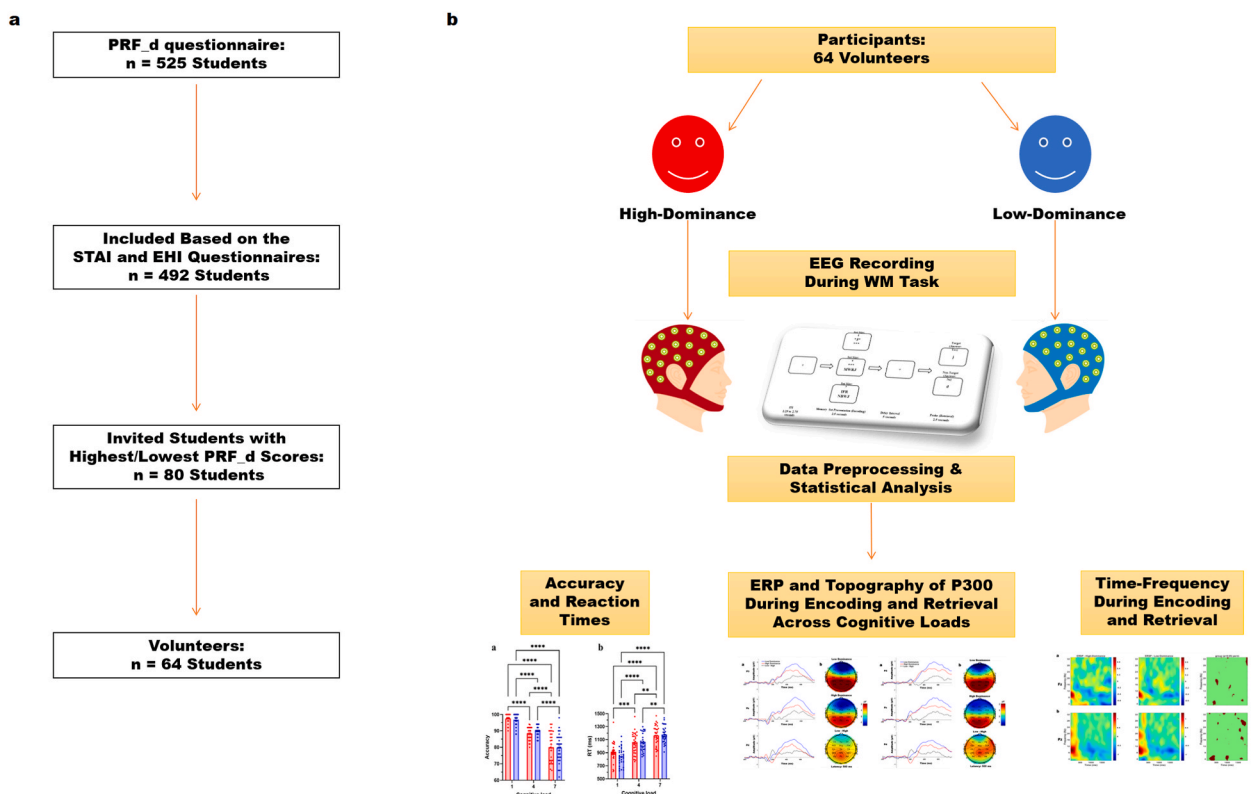


Fig. 1. a) Participant selection procedure b) Experimental procedure.

literature was found to separate individuals as high- or low-dominant based on this questionnaire, the decision was made to invite students from both ends of the spectrum. Therefore, students with the highest scores (ranging from 16 to 10) and the lowest scores (ranging from 1 to 7) in the PRF_d questionnaire were identified and invited to participate in the study. Out of the more than 80 subjects that were identified, 64 agreed to take part. It is worth noting that in the similar study conducted by Da Cruz et al. [21], individuals with scores ranging from 1 to 8 were classified as low-dominants and high-dominants with scores ranging from 9 to 16. However, in order to capture a wider range of individual differences, the choice was made not to invite participants with scores of 8 or 9, even though most participants fell within this range. The final sample for electrophysiological analysis consisted of 60 participants (31 high-dominance group, 29 low-dominance, 30 female, and 30 male), after excluding four participants due to noisy data and artifacts. For the behavioral analysis, data from two participants were missing, resulting in a total of 62 participants (32 high-dominance group, 30 low-dominance group, 32 female, and 30 male) whose data were included in the analysis. By employing these exclusion criteria and data cleaning procedures, the study aimed to ensure the integrity and quality of the collected data for both the electrophysiological and behavioral analyses.

2.2. Instruments

2.2.1. Personality research form dominance subscale

The tendency for social dominance was assessed in this study using the PRF_d questionnaire. The PRF_d is a 16-item true/false questionnaire that measures individuals' motivation for social dominance through a series of positive and negative statements, such as "My ability to be a leader is very important" and "I do not insist a lot in a debate" [21,50].

In this questionnaire, participants earn 1 point for each true statement indicating dominance, while the reverse statements are also considered. Half of the questions are positive, such as "I would make a poor military leader," meaning participants receive 1 point for each true statement and 0 points for each false one. Conversely, the other half consists of opposite statements, where participants earn 1 point for each false statement and 0 points for each true one. This scoring system allows their overall score to be calculated out of a total of 16.

Reliability and validity analyses have been conducted to assess the psychometric properties of the PRF_d questionnaire. In an intercultural study utilizing 17 different statistical samples, the coefficient of congruence across North America, Europe, and an Asian country (Philippines) was found to be 0.93, indicating a high level of consistency [51]. Moreover, in our previous studies, Cronbach's alpha and McDonald's omega coefficients were calculated for this questionnaire to be 0.730 and 0.729, respectively [7,8]. These coefficients reflect the internal consistency of the questionnaire and indicate desirable reliability. The reliability and validity analyses suggest that the PRF_d questionnaire provides a robust measure of individuals' tendency for social dominance, supporting its suitability for use in the present study.

2.2.2. Working memory task

The test employed in this study to examine WM function was a task-based version of the Sternberg paradigm. During the task, neutral alphabet letters were presented without any semantic, emotional, or social context, ensuring that participants focused solely on memorization (encoding) and recall (decoding/retrieval) processes [23]. Initially, a positive or plus sign (+) was displayed as a

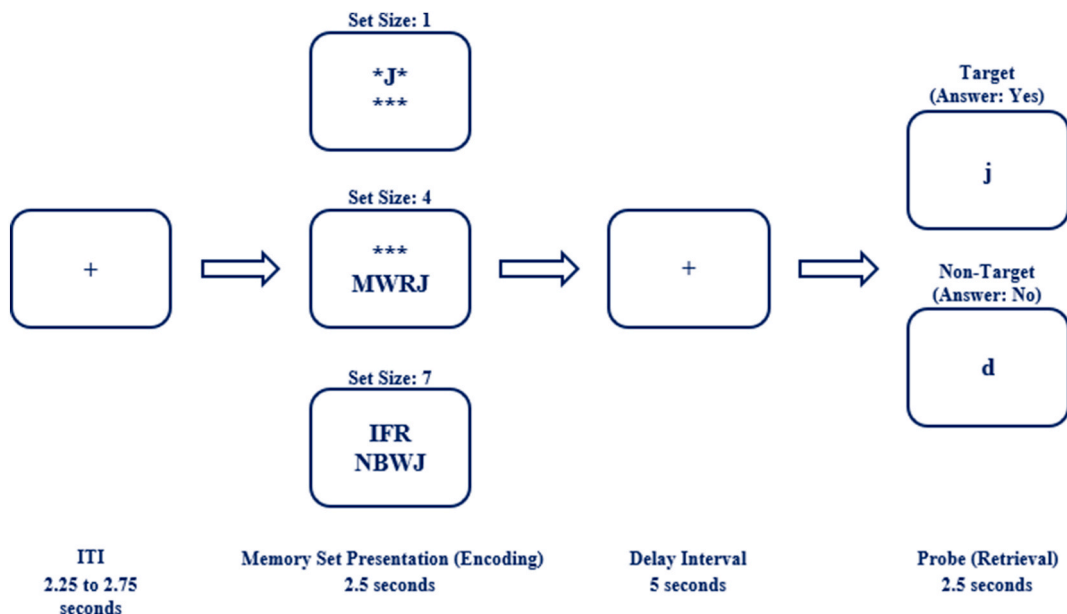


Fig. 2. Diagram of WM task in Sternberg paradigm illustrating one single trial. Asterisk shows absent letter in an array.

fixation point for a duration of 2.25–2.75 s. Following the fixation point, random alphabet letters were presented during the memorization phase. These letters were presented in sets of 1, 4, or 7, and participants had 2.5 s to memorize them in a random order. After the memorization phase, a 5-s delay period with the fixation point allowed for the retention of the memorized information. Subsequently, during the retrieval phase, participants were presented with a target or non-target letter for 2 s and had to determine whether it was the target (correct response) or non-target (wrong response) by pressing the corresponding button (Fig. 2).

Each trial had a duration of 12 s, and a total of 180 trials were conducted, divided into 6 blocks of 30 trials each. The set sizes of 1, 4, and 7 were presented 10 times within each block, resulting in 60 presentations for each set size. Within each block, there were 5 target words and 5 non-target words. To prevent fatigue, a 1-min break was provided between each block. The data analysis focused on the 5 blocks (150 trials) after excluding the initial practice blocks, aiming to eliminate the influence of the learning process associated with the task. Participants were instructed to respond as quickly and accurately as possible, and no feedback on their performance was provided [23].

It is important to note that the task required participants to manipulate information in their WM. In the encoding (memorization) phase, uppercase letters were presented, while in the retrieval (recalling) phase, participants were asked to identify lowercase letters. This required participants to mentally transform the information by converting the capital letters to lowercase letters in order to provide a response. Thus, the task specifically assessed the storage and manipulation of information in WM, rather than simply measuring recognition memory or short-term memory. It is worth mentioning that the manipulation involved in this task was considered a low-level manipulation.

2.3. Procedure

Following the questionnaire completion and participant recruitment process described earlier, students were enlisted to perform the experimental WM task while their EEG signals were recorded. The two participant groups were carefully matched in terms of gender and age, with 17 females in each group. The mean age of the high-dominant group was 23.09 (SD = 4.07), while the mean age of the low-dominant group was 23.90 (SD = 4.45). In the subsequent statistical analysis, the effect of gender was included as a control variable to account for any potential influence. To ensure comparability and control for potential confounding factors, additional measures were taken. Firstly, intelligence was controlled by specifically selecting university students who had gained admission through a highly competitive national entrance exam. This exam admits only a limited number of highly competitive students, ensuring a consistent level of intelligence among the participants.

Furthermore, all participants were students of engineering or science programs to control for educational background. The participants' physical and mental health status, as well as any medication usage, were controlled by exclusively including healthy individuals as subjects. Additionally, participants were asked about their sleeping hours the night before the experiment, and efforts were made to match the sleep duration between the two groups. To minimize potential confounding effects, participants were instructed not to consume caffeinated beverages, such as coffee, within 8 h before the test, and to abstain from consuming alcoholic beverages for 24 h prior to the test.

Environmental conditions during the EEG recordings were meticulously controlled. The recordings took place between 3 p.m. and 7 p.m. to ensure consistent daylight conditions. The temperature in the recording room was maintained at approximately 24 °C. Moreover, strict measures were implemented to minimize external disturbances, such as prohibiting entry into the recording room and ensuring no loud noises were present in the vicinity.

By implementing these rigorous control measures, the study aimed to minimize potential confounding factors and create a controlled experimental environment, enhancing the reliability and validity of the results. The experimental task was administered using eevolve™ software (ANT Neuro, Enschede, Netherlands). EEG signals were continuously recorded using a 64-channel system with a waveguard™ cap (ANT Neuro, Enschede, Netherlands) following the international 10-10 system for electrode placement. To maintain a stable reference, the EEG signals were referenced to the average activity of two mastoid electrodes. The signals were digitized at a sampling rate of 250 Hz to ensure accurate representation of the EEG waveform. To ensure reliable signal quality, the impedance of all electrodes was kept below 10 K Ω .

Following data collection, four participants were excluded from the analysis due to noisy data and extreme eye artifacts, which could potentially affect the reliability of the EEG recordings. Consequently, the data from 60 individuals were retained for further analysis, ensuring a high-quality dataset for examining the electrophysiological correlates of the WM task.

2.4. Data analysis

2.4.1. Behavioral data analysis

Participants' WM performance was assessed based on accuracy, which represents the percentage of correct responses out of the total responses, and reaction times (RTs), which indicate the time taken to respond and press the button. Mean accuracy and mean RTs were computed for each participant and used in the subsequent analyses.

For the analysis of covariance (ANCOVA), both mean accuracy and mean RTs were considered as dependent variables. The *group* (high-dominance group and low-dominance group) served as the fixed factor, while *gender* was included as a covariate and their main and interaction effects was probed. Furthermore, all responses were utilized in a repeated measures analysis of variance (RM-ANOVA). This analysis aimed to examine the effects of *group* (low-dominance, high-dominance), *cognitive load* (1, 4, 7), and their interaction (*group*cognitive load*) on behavioral measures. It did not assume sphericity and a Geisser-Greenhouse correction was applied.

2.4.2. Electrophysiological data analysis

2.4.2.1. ERP analysis. The ERP data analysis was performed using the EEGLAB 13 toolbox and the ERPLAB 6 plugin in the MATLAB 2014b. Prior to analysis, the data underwent several preprocessing steps. A high-pass filter with a cutoff frequency of 0.5 Hz and a low-pass filter with a cutoff frequency of 40 Hz were applied to reduce noise and focus on the relevant frequency range. To further enhance data quality, specific artifacts related to movement and eye-related noises were removed from the continuous EEG data. Independent component analysis (ICA) was utilized to identify and remove any remaining noise sources. The data were then segmented into epochs for subsequent analysis. Each epoch spanned from 200 ms before stimulus presentation to 800 ms after, and a baseline correction was applied using the interval 200 ms before the stimulus presentation. For each participant, the ERP was calculated by extracting the mean amplitude within the 300–800 ms time window after stimulus presentation. This analysis was performed for three electrodes: P3, Pz, and P4, which are known to capture the P3b component. The mean amplitude values were analyzed separately for the encoding and retrieval phases.

To conduct statistical analyses, the data from each participant were entered into IBM SPSS 26 software. The grand average of the two groups was plotted for each phase (encoding and retrieval), and brain topography was visualized by mapping voltage distribution at 500 ms after stimulus presentation. ANCOVA (analysis of covariance) was performed to analyze the mean amplitude of the P3b ERP component between 300 and 800 ms post-stimulus presentation during the encoding and retrieval phases. The fixed factors included the group (high-dominance group and low-dominance group) and gender as a covariate. Additionally, a RM-ANOVA was utilized to analyze the mean amplitude of the P3b ERP component between the encoding and retrieval phases as well as high- and low-dominance groups. Firstly, the fixed effects included the task phase (encoding, retrieval), cognitive load (1, 4, 7), and their interaction (task phase*cognitive load). Second, the fixed effects included the group (low-dominance, high-dominance), cognitive load (1, 4, 7), and their interaction (group*cognitive load). These statistical analyses aimed to investigate the differences in P3b amplitude between task phases and groups, taking into account gender and cognitive load as relevant factors. For post hoc comparisons, t-tests with Bonferroni correction were applied for multiple comparisons.

2.4.2.2. Time frequency analysis. The time frequency and power spectral analyses were completed using study menu and “spectopo” and “newtimef” functions and their default options (unless mentioned otherwise) using Morlet wavelets of EEGLAB following these parameters: [‘cycles’, [3 0.8], ‘nfreqs’, 100, ‘freqs’, [3 33], ‘freqscale’, ‘linear’, ‘ntimesout’, 200]. Utilizing the same EEG data for the ERP analysis epochs for each participant were categorized from 500 ms before stimulus presentation to 2500 ms after. In this regard, power spectral and ERSP analyses were used to measure fluctuations in spectral power across time domain in the related frequency bands. Main focus of this study was on theta (4–8 Hz), alpha (8-13), and beta (13–30) which are related to WM. For frontal and parietal regions ERS, ERD, and power spectrum figures of Fz and Pz electrodes together with their between-group statistically significant differences were computed and plotted. To address the problem of multiple comparisons, statistical unpaired permutation t-tests with FDR correction was utilized in the EEGLAB toolbox with a p-value of 0.05 (two-tailed) and automatic randomization. Note that power spectral analyses are provided in the supplementary materials section.

Correlational analyses were applied to investigate the potential association of behavioral data with electrophysiological results as well as the association between the encoding and the retrieval phases. To do so, Spearman’s rho test as well as simple linear regressions were employed.

3. Results

3.1. Behavioral results

The accuracy data exhibited a mean of 88.3 with a standard deviation of 4.31, as shown in Table 1. Similarly, the mean RTs were calculated as 1026 with a standard deviation of 135, as detailed in Table 1.

The results of ANCOVA on accuracy showed no significant main effect of group [$F(1, 58) = 0.04, p > 0.05, \eta_p^2 = 0.00$] or gender [$F(1, 58) = 2.19, p > 0.05, \eta_p^2 = 0.03$] and interaction effect of group*gender [$F(1, 58) = 0.45, p > 0.05, \eta_p^2 = 0.00$] suggesting no difference in accuracy between dominance or gender groups. Similarly, the results of ANCOVA on RTs showed no significant main effect of group [$F(1, 58) = 0.04, p > 0.05, \eta_p^2 = 0.00$] or gender [$F(1, 58) = 0.20, p > 0.05, \eta_p^2 = 0.00$] and interaction effect of

Table 1 Behavioral and electrophysiological data descriptive.

Behavioral Data	PRF_d		Accuracy		RT	
N	High-Dominants: 33 (F = 17, M = 16)		Low-Dominants: 31 (F = 17, M = 14)		-	-
Mean	12.76		5.67		88.3	1026
Standard deviation	1.82		1.62		4.31	135
Electrophysiological Data	Encoding Amplitude at P3	Encoding Amplitude at Pz	Encoding Amplitude at P4	Probing Amplitude at P3	Probing Amplitude at Pz	Probing Amplitude at P4
Mean	3.16	3.48	2.98	3.25	3.37	3.01
Standard deviation	2.11	2.12	2.38	2.20	2.37	2.21

$group * gender$ [$F(1, 58) = 0.26, p > 0.05, \eta_p^2 = 0.00$] suggesting no difference in RTs between dominance or gender groups.

However, the results of ANOVA with cognitive load as a within-group factor showed that there were significant within-group differences of accuracy [$F(2, 171) = 131.30, p < 0.0001, \eta_p^2 = 0.005$, Fig. 3a] and RT [$F(2, 180) = 67.51, p < 0.0001, \eta_p^2 = 0.005$, Fig. 3b] across different cognitive loads from 1 to 7 set-sizes.

3.2. Electrophysiological results

3.2.1. ERP results during encoding phase

The results of ANCOVA on mean amplitude of P3, Pz, and P4 electrodes during the encoding phase revealed a significant main effect of $group$ and $group * gender$. Specifically, for the P3 electrode, there was a significant main effect of $group$ [$F(1, 56) = 17.16, p < 0.001, \eta_p^2 = 0.23$] and interaction effect of $group * gender$ [$F(1, 56) = 5.12, p < 0.05, \eta_p^2 = 0.08$] but no main effect of $gender$ [$F(1, 56) = 2.02, p > 0.05, \eta_p^2 = 0.03$]. Additionally, for the Pz electrode, the main effect of $group$ [$F(1, 56) = 14.01, p < 0.001, \eta_p^2 = 0.19$] was also significant and interaction effect of $group * gender$ [$F(1, 56) = 2.81, p > 0.05, \eta_p^2 = 0.04$] had an insignificant trend and there was no main effect of $gender$ [$F(1, 56) = 2.09, p > 0.05, \eta_p^2 = 0.03$]. Similarly, for the P4 electrode, the main effect of $group$ yielded a significant result [$F(1, 56) = 13.49, p < 0.001, \eta_p^2 = 0.19$] and interaction effect of $group * gender$ [$F(1, 56) = 3.25, p > 0.05, \eta_p^2 = 0.05$] had an insignificant and marginal trend and there was no main effect of $gender$ [$F(1, 56) = 0.64, p > 0.05, \eta_p^2 = 0.01$].

These findings indicate a significant difference in the mean amplitude of P3b component between the high- and low-dominant groups during encoding phase. Notably, the amplitude was higher in low-dominant group compared to the high-dominant group (Fig. 4a). These differences were consistent across all three electrodes and the effect sizes were large ($\eta_p^2 > 0.14$) for all three electrodes. Importantly, this group difference remained significant even when gender was controlled (see supplementary for figures regarding gender differences within groups). The scalp's topographical maps depict the distribution of voltage for low-dominance group (top), high-dominance group (middle), and their difference (bottom) during encoding phase at 500 ms post stimulus presentation in the WM task (Fig. 4b).

3.2.2. ERP results during retrieval phase

The results of ANCOVA on mean amplitude of P3, Pz, and P4 electrodes during the retrieval phase revealed a significant main effect of $group$ and $group * gender$. Specifically, for the P3 electrode, there was a significant main effect of $group$ [$F(1, 56) = 12.02, p < 0.001, \eta_p^2 = 0.17$] and interaction effect of $group * gender$ [$F(1, 56) = 4.13, p < 0.05, \eta_p^2 = 0.06$] but no main effect of $gender$ [$F(1, 56) = 0.40, p > 0.05, \eta_p^2 = 0.00$]. Additionally, for the Pz electrode, the main effect of $group$ [$F(1, 56) = 11.69, p < 0.001, \eta_p^2 = 0.17$] was significant and interaction effect of $group * gender$ [$F(1, 56) = 3.74, p > 0.05, \eta_p^2 = 0.06$] had an insignificant marginal trend and there was no main

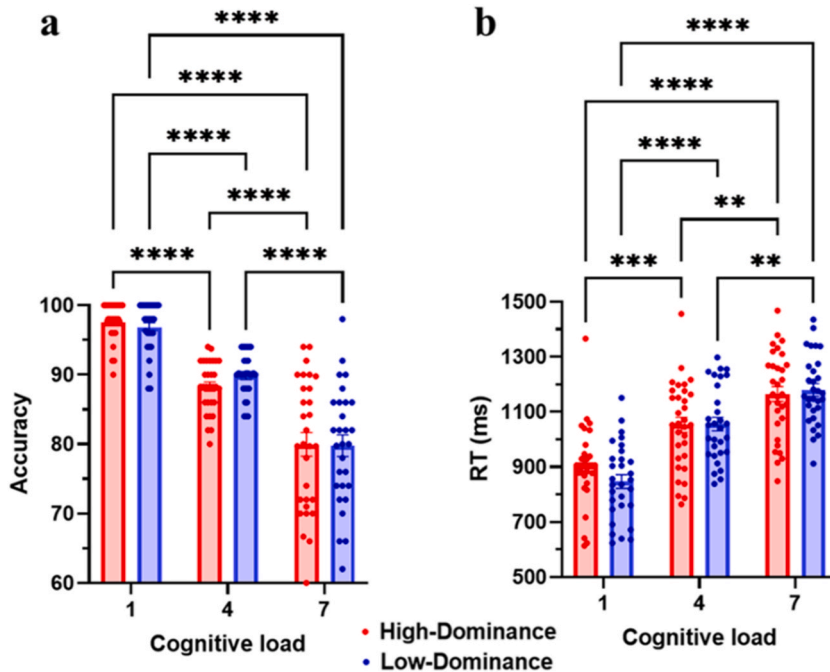


Fig. 3. Behavioral results indicates that accuracy decreases and RT increases as difficulty (cognitive load) of the task increases. However, there is not any difference between high-dominance group and low-dominance group in the behavioral level. ** $p < 0.01$, *** $p < 0.001$, **** $p < 0.0001$.

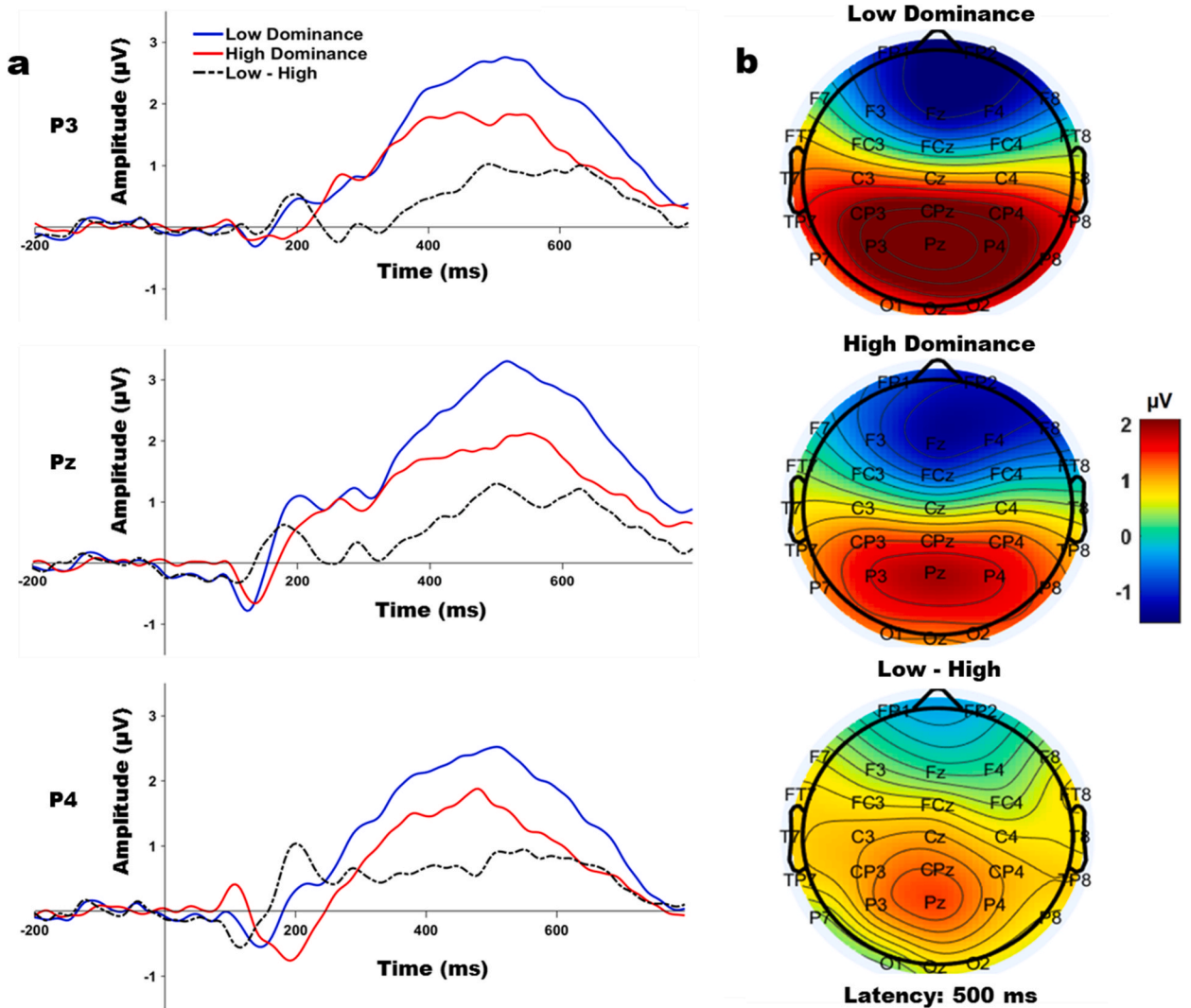


Fig. 4. a) P3b ERP component of high-dominance group (red) and low-dominance group (blue) during encoding phase in WM task at P3, Pz and P4 electrodes. Results revealed higher amplitude for low-than high-dominance group. b) Scalp’s topographical maps of low-dominance group (top), and high-dominance group (middle), and their difference (bottom) during encoding phase at 500 ms post stimulus presentation in the WM task.

effect of *gender* [$F(1, 56) = 0.72, p > 0.05, \eta_p^2 = 0.01$]. Similarly, for the P4 electrode, the main effect of *group* yielded a significant result [$F(1, 56) = 5.96, p < 0.01, \eta_p^2 = 0.09$] and interaction effect of *group*gender* [$F(1, 56) = 3.01, p > 0.05, \eta_p^2 = 0.05$] had an insignificant trend and there was no main effect of *gender* [$F(1, 56) = 0.21, p > 0.05, \eta_p^2 = 0.00$].

These findings indicate a significant between-group difference in the mean amplitude of P3b ERP component, with higher amplitudes observed in the low-dominant group as compared to high-dominant group during retrieval phase (Fig. 5a). The effect sizes were large for P3 and Pz electrodes ($\eta_p^2 > 0.14$) and medium for the P4 electrode ($\eta_p^2 > 0.06$). Importantly, this group difference remained significant even when gender was controlled (see supplementary for figures regarding gender differences within groups). The scalp’s topographical maps depict the distribution of voltage for low-dominance group (top), high-dominance group (middle), and their difference (bottom) during retrieval phase at 500 ms post stimulus presentation in the WM task (Fig. 5b).

3.2.3. ERP results across different cognitive loads during encoding and retrieval phases

The RM-ANOVA demonstrated a significant main effect of *task phase* in P3 [$F(1, 59) = 27.05, p < 0.0001$], Pz [$F(1, 59) = 14.93, p < 0.0005$], and P4 [$F(1, 59) = 6.27, p < 0.05$] and interaction effect of *task phase*cognitive load* in P3 [$F(1.876, 110.7) = 5.98, p < 0.005$], Pz [$F(1.703, 100.5) = 12.40, p < 0.0001$], and P4 [$F(1.928, 113.8) = 4.05, p < 0.05$] as well as a significant main effect of *cognitive load* in Pz [$F(1.799, 106.1) = 11.43, p < 0.0001$]. These results indicate that the mean amplitude of P3b significantly increased when *task phase* changed from the encoding to the retrieval among all participants.

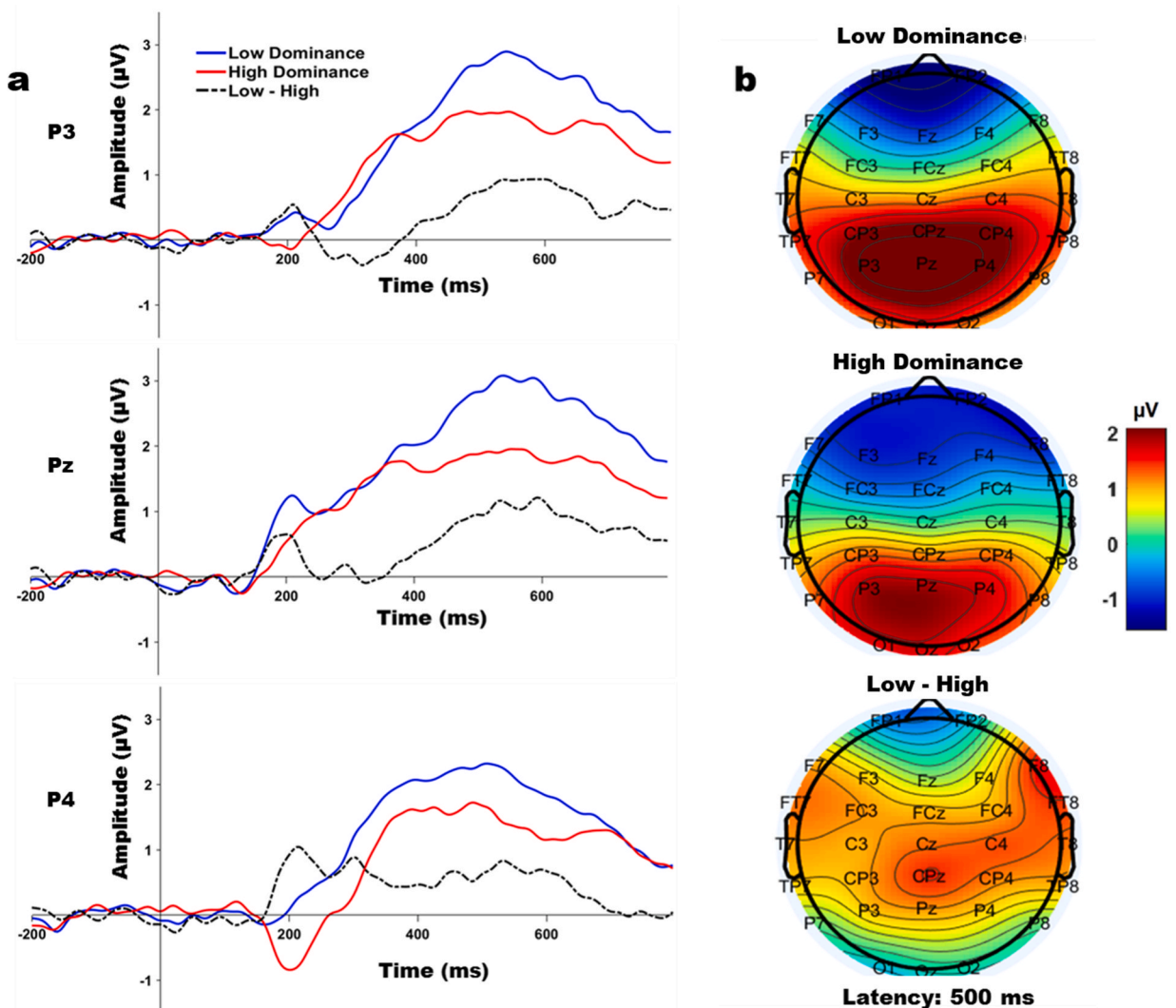


Fig. 5. a) P3b ERP component of high-dominance group (red) and low-dominance group (blue) during retrieval phase in WM task at P3, Pz and P4 electrodes. Results revealed higher amplitude for low-than high-dominance group. b) Scalp's topographical maps of low-dominance group (top), and high-dominance group (middle), and their difference (bottom) during retrieval phase at 500 ms post stimulus presentation in the WM task.

Additionally, the post hoc comparisons with t -tests showed that during encoding phase when *cognitive load* increased from 1 to 4, the mean amplitude of P3b significantly increased in P3 ($t(59) = 3.38, p < 0.05$, Fig. 6a), Pz ($t(59) = 4.43, p < 0.001$, Fig. 6b), and P4 ($t(59) = 3.18, p < 0.05$, Fig. 6c) electrodes. In contrast, the amplitude decreased when *cognitive load* increased from 4 to 7 in P3 ($t(59) = 3.20, p < 0.05$, Fig. 6a) and Pz ($t(59) = 4.18, p < 0.005$, Fig. 6b) electrodes but not in P4 ($t(59) = 1.96, p > 0.05$, Fig. 6c). Simultaneously, no significant differences were observed when *cognitive load* increased from 1 to 4 in P3 ($t(59) = 0.09, p > 0.05$), Pz ($t(59) = 0.26, p > 0.05$), and P4 ($t(59) = 0.09, p > 0.05$) electrodes as well as from 4 to 7 in P3 ($t(59) = 0.09, p > 0.05$), Pz ($t(59) = 2.07, p > 0.05$), and P4 ($t(59) = 0.09, p > 0.05$) electrodes. Moreover, observed increase of mean amplitude of the P3b when *task phase* switched from the encoding to the retrieval was originated from differences of conditions with *cognitive load* of one ($t(59) = 4.06, p < 0.005$) and seven ($t(59) = 3.11, p < 0.05$) in P3, one ($t(59) = 5.49, p < 0.0001$) in Pz, and four ($t(59) = 3.57, p < 0.05$) in P4 electrode.

These results indicate there were differences in mean amplitude of P3b component of all participants at different cognitive loads during the encoding but not the retrieval phase. Remarkably, the observed pattern of the P3b during the encoding phase exhibited a concave shape resembling an inverted U. This pattern signifies that as the cognitive load progressively increased, the mean amplitude of the P3b component showed a corresponding increase from cognitive load of 1–4 among all participants. However, beyond cognitive load of 4, the mean amplitude of the P3b component started to decline.

Furthermore, the RM-ANOVA for the amplitude of P3b during encoding phase revealed a significant main effect of *group* and *cognitive load* in P3 [$F(1, 58) = 23.35, p < 0.0001, F(1.77, 102.4) = 23.87, p < 0.0001$, Fig. 7a], Pz [$F(1, 58) = 16.47, p < 0.0001, F(1.57, 91.03) = 16.19, p < 0.0001$, Fig. 7b], and P4 [$F(1, 58) = 17.06, p < 0.0001, F(1.58, 91.67) = 15.48, p < 0.0001$, Fig. 7c]

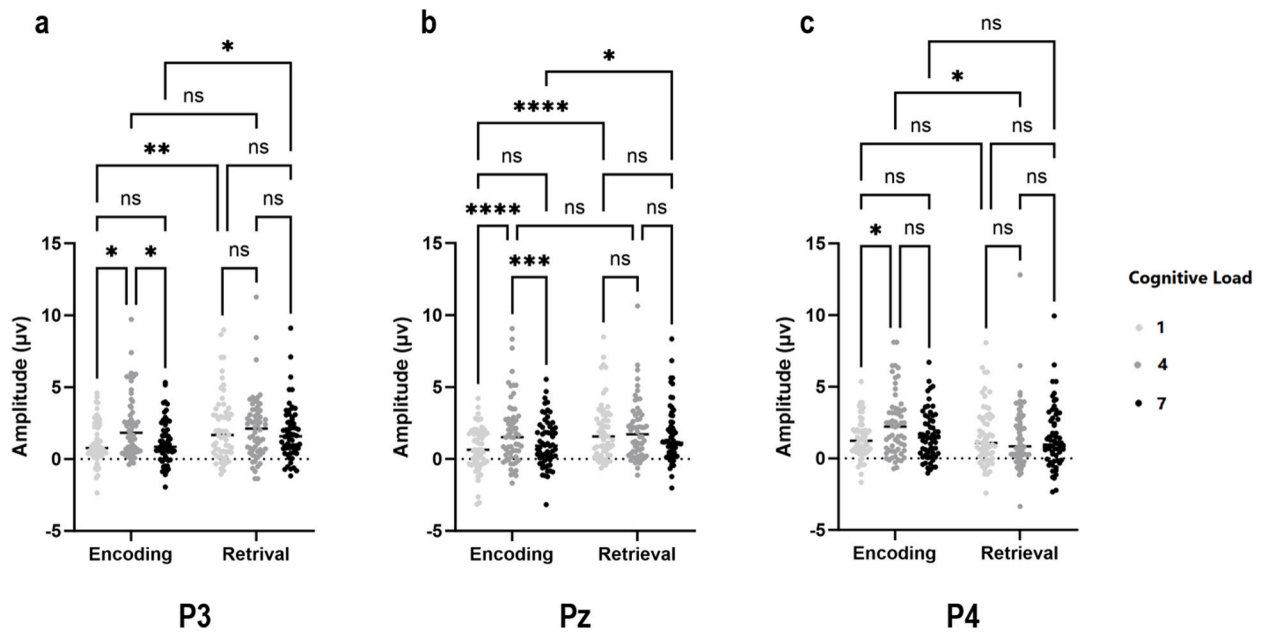


Fig. 6. Graph of P3b ERP component illustrated in mean amplitude by cognitive load during encoding phase and retrieval phase at P3 (a), Pz, (b) and P4 (c) electrodes. The mean amplitude changes by switching between different cognitive loads among all participants. * $p < 0.05$, ** $p < 0.005$ *** $p < 0.0005$, **** $p < 0.0001$.

electrodes. Also, it indicated a significant interaction effect of *group*cognitive load* in P3 [$F(2, 116) = 6.51, p < 0.005$] and P4 [$F(2, 116) = 3.18, p < 0.05$] electrodes and an insignificant trend in Pz [$F(2, 116) = 1.63, p > 0.05$].

Additionally, post hoc comparisons with *t*-tests showed low-dominants had greater mean amplitude of P3b than high-dominants in

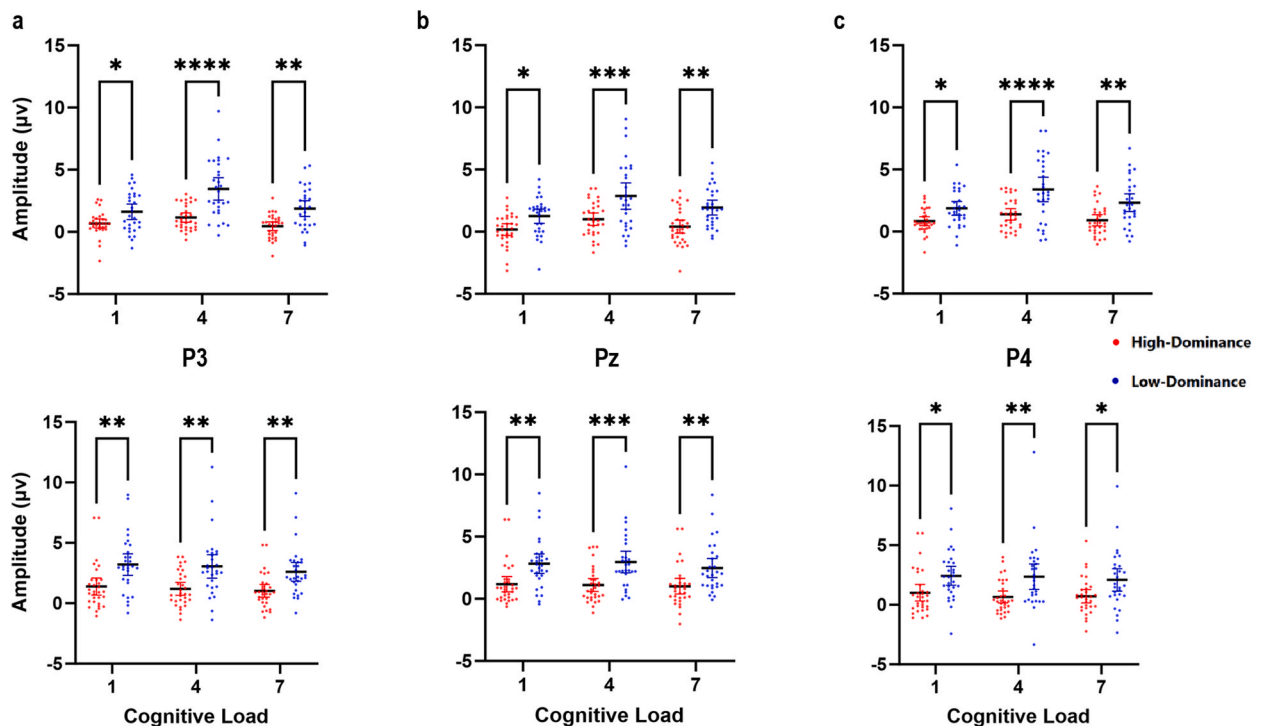


Fig. 7. Graphs of P3b ERP component illustrated in mean amplitude by cognitive load during encoding phase (top) and retrieval phase (bottom) at P3 (a), Pz (b), and P4 (c) electrodes. Results revealed higher amplitude for low- than high-dominant group in all conditions. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.005$, **** $p < 0.001$.

all three electrodes of P3 [one: $t(45.54) = 2.68, p < 0.05$, four: $t(37.60) = 4.85, p < 0.0001$, seven: $t(43.82) = 4, p < 0.001$], Pz [one: $t(54.81) = 2.98, p < 0.05$, four: $t(40.33) = 3.26, p < 0.01$, seven: $t(56.66) = 3.93, p < 0.001$], and P4 [one: $t(47.98) = 3.20, p < 0.01$, four: $t(39.89) = 3.78, p < 0.005$, seven: $t(47.66) = 3.42, p < 0.005$] across all three cognitive loads (1, 4, and 7 respectively) during the encoding phase.

These findings suggest a remarkable between-group difference in the mean amplitude of P3b ERP component at various cognitive loads with low-dominance group exhibiting higher amplitudes compared to high-dominance group in all conditions (Fig. 7, top). Notably, there is an inverted U shape pattern, indicating that as cognitive load increases from 1 to 4 and 4 to 7, the mean amplitude of P3b component first increases and then decreases within each group (high- and low-dominance group).

Finally, the RM-ANOVA for the amplitude of P3b during retrieval phase revealed a significant main effect of *group* and *cognitive load* in P3 [$F(1, 58) = 12.94, p < 0.001, F(1.96, 113.5) = 5.92, p < 0.005$, Fig. 7a], and *group* in Pz [$F(1, 58) = 12.92, p < 0.001$, Fig. 7b], and P4 [$F(1, 58) = 8.73, p < 0.005$, Fig. 7c] electrodes. Also, there was an insignificant but marginal trend of cognitive load in Pz [$F(1.97, 114.1) = 2.78, p > 0.05$] and P4 [$F(1.83, 106) = 2.30, p > 0.05$]. Also, it indicated an insignificant interaction effect of *group***cognitive load* in P3 [$F(2, 116) > 0.05, p > 0.05$], Pz [$F(2, 116) = 1.02, p > 0.05$], and P4 [$F(2, 116) = 0.70, p > 0.05$].

Additionally, post hoc comparisons with *t*-tests showed low-dominants had greater mean amplitude of P3b than high-dominants in all three electrodes of P3 [one: $t(54.19) = 3.28, p < 0.01$, four: $t(43.48) = 3.45, p < 0.005$, seven: $t(49.93) = 3.43, p < 0.005$], Pz [one: $t(54.25) = 3.35, p < 0.005$, four: $t(46.42) = 3.73, p < 0.005$, seven: $t(54.83) = 3.01, p < 0.05$], and P4 [one: $t(56.52) = 2.74, p < 0.05$, four: $t(40.01) = 2.94, p < 0.05$, seven: $t(46.07) = 2.56, p < 0.05$] across all three cognitive loads (1, 4, and 7 respectively) during the retrieval phase.

These findings suggest a notable between-group difference in the mean amplitude of P3b ERP component at different cognitive loads, with low-dominance group exhibiting higher amplitudes compared to high-dominance group in all conditions (Fig. 7, bottom).

3.2.4. Time frequency results during encoding phase

Time frequency analysis is done for data epoch 500 ms before the stimulus presentation to 2500 ms after in encoding phase. Permutation unpaired *t*-tests revealed a significant event-related synchronization (ERS) in theta and beta bands suggesting a significant between group differences with high-dominance group exhibiting higher theta and beta ERS during the time course of P3b ERP component (300–800 ms post-stimulus presentation) in frontal (Fig. 8a) and parietal (Fig. 8b) regions.

3.2.5. Time frequency results during retrieval phase

Time frequency analysis is done for data epoch 500 ms before the stimulus presentation to 2500 ms after in retrieval phase. Permutation unpaired *t*-tests revealed a significant event-related synchronization (ERS) in beta band suggesting a significant between group differences with high-dominance group exhibiting higher beta ERS during the time course of P3b ERP component (300–800 ms post-stimulus presentation) in frontal (Fig. 9a) and parietal (Fig. 9b) regions.

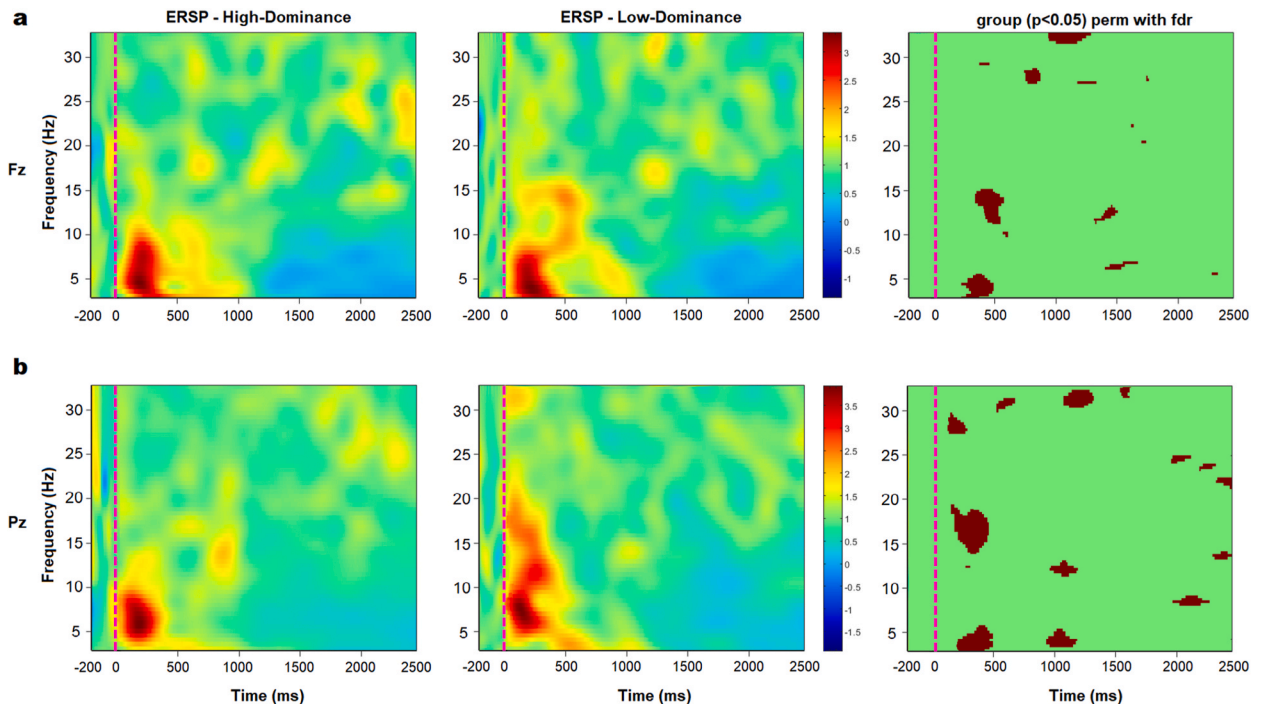


Fig. 8. ERSP results in Fz (a) and Pz (b) electrodes for high (left panel) and low (middle panel) dominance group and the between groups difference (right panel) during stimulus presentation [-200, 2500 ms] in the encoding phase. Brown color on the right panels indicate $p < 0.05$.

3.2.6. Correlational analyses

The results of simple linear regressions showed that there were statistically significant association of the encoding and the retrieval phases during cognitive loads of one ($F(1, 58) = 26.57, p < 0.0001, R^2 = 0.31$, Fig. 10a), four ($F(1, 58) = 78.13, p < 0.0001, R^2 = 0.57$, Fig. 10b), and seven ($F(1, 58) = 35.86, p < 0.0001, R^2 = 0.38$, Fig. 10c) in Pz electrode which is the main electrode to observe P3b component.

These results indicate that the amplitude of P3b during the encoding phase accounted for approximately 31 %, 57 %, and 38 % of the variance in the amplitude of P3b across cognitive loads of one, four, and seven during the retrieval phase among all participants. These effect sizes were considered to be large effects, emphasizing the important role that the effort during the encoding of the information played in remembering items later.

In the same way, there was a statistically significant association of the amplitude of P3b during the encoding and the retrieval phases within high-dominant ($F(1, 91) = 24.06, p < 0.0001, R^2 = 0.21$) and low-dominant ($F(1, 85) = 51.00, p < 0.0001, R^2 = 0.38$) groups separately in Pz electrode (Fig. 10d). These effect sizes were considered to be large effects suggesting the substantial role of the effort during the encoding of the information played in remembering items later within low-dominant and high-dominant groups separately.

Similarly, the results of an RM-ANOVA on Pz data supported these within-group differences (within each dominance group) as well as between-group differences (between encoding and retrieval). It revealed significant main effect of the group ($F(1, 58) = 16.80, p < 0.0001$) and task phase ($F(1, 58) = 14.86, p < 0.0005$) as well as insignificant interaction ($F(1, 58) = 0.26, p > 0.05$) between them (Fig. 10e). Additionally, post hoc comparisons with t-tests showed that low-dominants had a significantly lower amplitude of P3b during the encoding phase ($t(116) = 3.55, p < 0.005$) and the retrieval phase ($t(116) = 3.96, p < 0.0005$).

These results suggest that both groups have greater amplitudes during the retrieval than the encoding phase and low-dominants had greater amplitude than high-dominants during both phases.

The results of Spearman's rho correlation test on behavioral and ERP measures revealed a negative correlation existed between accuracy and RT ($r = -0.56, p < 0.05$), whereby higher accuracy was linked to faster (lower) RT. Conversely, there was not a correlation between behavioral measures and ERP P3b amplitudes across all electrodes. Lastly, there was a noteworthy positive correlation between P3b amplitudes during the encoding and retrieval phases across all electrodes (Fig. 10f).

4. Discussion

In this study, we were interested in evaluation of differences in the electrophysiological and behavioral measures of WM between high-dominant and low-dominant individuals. We will first discuss the behavioral findings, followed by the electrophysiological results.

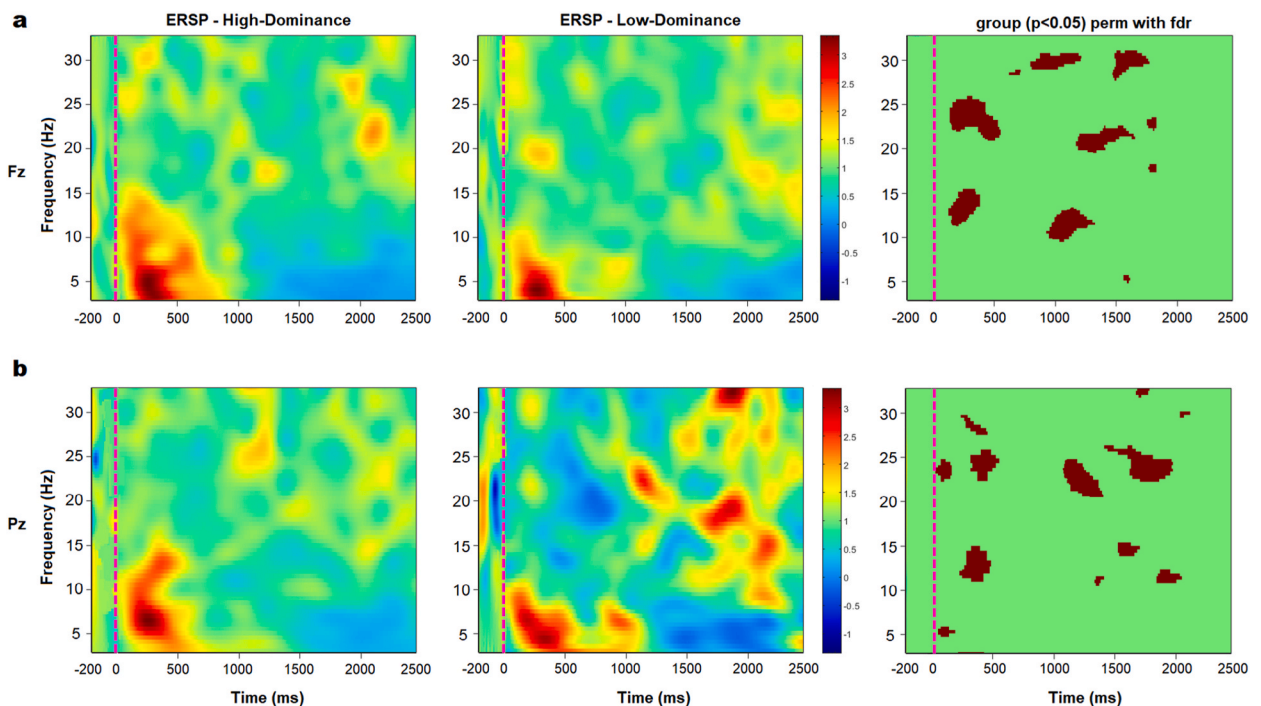


Fig. 9. ERSP results in Fz (a) and Pz (b) electrodes for high (left panel) and low (middle panel) dominance group and the between groups difference (right panel) during stimulus presentation [-200, 2500 ms] in the retrieval phase. Brown color on the right panels indicate $p < 0.05$.

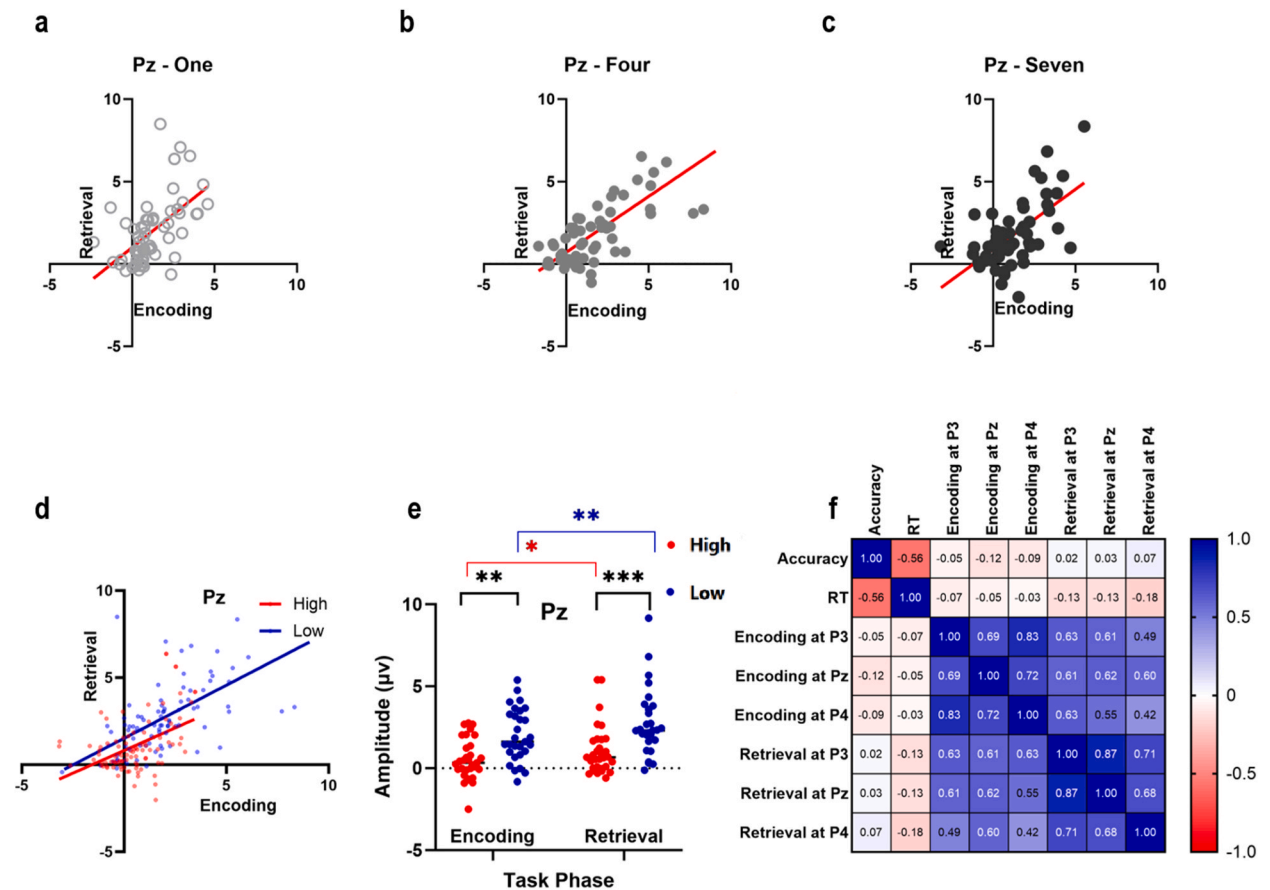


Fig. 10. Simple linear regressions (a, b, c, d), repeated measures two-way ANOVA (e), and correlation matrix (f) for association of behavioral and ERP results as well as the association between the encoding and retrieval phases.

4.1. Behavioral findings

Contrary to our hypotheses, we did not find significant differences in response accuracy and RT between the high-dominance and low-dominance groups. These results suggest that behavioral performance of both groups in the WM task was the same. One possible explanation for the lack of behavioral differences in spite of electrophysiological differences, is the level of cognitive load and task difficulty. Previous research suggests that individual differences in WM become more apparent under higher cognitive load conditions [52,53]. For instance, children from low socioeconomic backgrounds exhibit greater functional activation in response to higher cognitive load of executive functions tasks [12,13]. In the current study, the cognitive load was manipulated by varying the number of items to be remembered (1, 4, or 7), which falls within the WM capacity of the general population. Additionally, participants had sufficient time intervals between the encoding and retrieval phases (5 s) and response periods (2 s). These factors likely contributed to a less complex and challenging task, making it easier for participants to perform. As a result, individual differences in behavioral performance were not discernible. Animal studies on WM suggests that a longer delay between the encoding and retrieval phases necessitates enhanced coordination within the hippocampus-PFC circuit to achieve accurate memory representation and facilitate goal-oriented processes [54]. Therefore, when this circuit's coordinated activity is challenged by more difficult tasks, individual differences in WM performance become more apparent.

These findings align with the study of Da Cruz et al., which demonstrated that high-dominant individuals exhibit faster responses in tasks with higher cognitive demands without compromising accuracy. In contrast, this dominance-related difference was not observed in simpler tasks that were less demanding. It is possible that our WM task resembled the latter scenario, lacking sufficient difficulty to reveal behavioral performance discrepancies between high- and low-dominant participants.

4.2. ERP findings

Moving on to the electrophysiological findings, our study confirmed a significant relationship between the dominance trait and the mean amplitude of the P3b component as well as ERS, which serves as a measure of WM activity. Specifically, we observed significantly lower mean amplitudes of the P3b ERP component and higher ERS of theta, and beta in high-compared to low-dominant

individuals during the encoding and retrieval phases of the task.

Amplitude of ERP is equivalent to the amount of neural activation in functional magnetic resonance imaging (fMRI) studies, and can be interpreted as the neural efficiency of information processing [23]. This means high-dominance group activate and use less neural resources for processing information, which is compatible with the idea that they allocate less cognitive resources to perform WM tasks as reflected by the P3b amplitude. In fact, high-dominance group use less cognitive and neural resources to perform behaviorally the same as low dominants. As a result, high-dominant individuals appear to be able to maintain information in WM easier. This finding supports previous studies showing positive correlations between social hierarchies and memory [22,52] and also provides the first neural evidence in humans for the dominance trait, as one dimension of social hierarchies. It also suggests that previous studies showing that high-dominance group make faster decisions in memory and emotional tasks may be due to their higher WM capabilities [21].

The amplitude of the P3b ERP component is also associated with the allocation of cognitive resources. Our findings suggest that WM tasks are easier for high-dominant individuals, as they require fewer cognitive resources compared to low-dominant individuals. This interpretation is supported by the results of the cognitive load and group by cognitive load. We observed distinct patterns of the P3b ERP component during the encoding phase, which were consistent within each group. Specifically, an inverted U shape pattern was observed during the encoding phase. These patterns resemble those reported in the study from which our experimental WM task was derived [23].

This pattern aligns with findings from previous ERP studies that have similarly identified inverted U-shaped relationships between P3b amplitude and cognitive load or task difficulty [23,55,56]. Specifically, our results indicate that WM tasks are less cognitively demanding for high-dominant individuals compared to their low-dominant counterparts. This interpretation is strongly supported by the distinct P3b patterns we observed during the encoding phase, which align with existing literature. Notably, these patterns resemble those identified in studies focused on cognitive reserve and WM, suggesting that our findings contribute to a broader understanding of how cognitive resources are allocated in different individuals based on task demands.

Further exploration of the reversed U-shaped pattern reveals several potential explanations. It may represent an optimal level of arousal necessary for maximizing P3b amplitude, consistent with the Yerkes-Dodson law, which suggests that performance improves with increasing arousal to an optimal point before declining [57]. Alternatively, individual differences in WMC and strategy use might explain the variance in P3b amplitudes—participants with moderate capacity may engage more effectively, while those at the extremes may not allocate resources optimally [58]. Moreover, this pattern might indicate differing neural processes engaged at various levels of task difficulty; moderate cognitive loads may optimally engage certain neural networks for encoding, whereas lower or higher loads may trigger alternate compensatory mechanisms and different networks, leading to reduced P3b amplitudes [59]. Together, these perspectives provide a possible framework for understanding the observed P3b amplitude patterns in relation to cognitive load and individual differences in memory capacity that warrants further exploration in future studies.

It is noteworthy that our study aligns with a moderate view that considers WM as both a stable trait and a state variable influenced by various contexts, including social factors such as dominance trait. Related research suggests that working memory capacity (WMC) is a relatively stable trait with high rates of reliability and validity. For example [60], found that visual WMC remained stable over time, even after extensive practice. Similarly [61], noted that domain-general WMC demonstrates established reliability and validity during different stages of measurements. While WMC has traditionally been viewed as a constant trait, some studies indicate potential for alterations [62]. reported that adaptive WM training can lead to increased capacity, associated with changes in brain activity and dopamine receptor density. However, the overall evidence suggests that WMC is mainly a stable trait known as an individual difference, while [61] characterizes it as both a trait and state variable, highlighting its enduring nature while acknowledging potential for short-term fluctuations.

Additionally, we cannot rule out the possibility that WMC might contribute to these results, as it would require the inclusion of another WM task such as spanning or N-back paradigms to be completed. While incorporating additional tasks alongside the main task in psychological studies raises concerns about variables such as fatigue and order effects [63]. Consequently, we were unable to directly investigate this aspect, and further research is necessary before firm conclusions can be drawn.

Still, to understand why high-dominant individuals may find it easier to memorize and recall information, we need to examine the factors underlying P3b amplitude and identify which factor plays the most significant role. The amplitude of P3b is determined by three factors: P (subjective probability), M (stimulus meaning), and T (amount of transmitted information) [64].

$$P300 \text{ amplitude} = f [T \times (1/P + M)]$$

In our study, the memorized information was the same for both groups, ruling out the T factor as the cause of the observed results. The next factor influencing P3b amplitude is P, which represents the objective probability of stimulus appearance. Since the stimuli were randomly presented in our task, their probability of appearance was the same for both groups, ruling out the P factor as well. Finally, M stands for the meaning of the stimuli, encompassing variables such as task complexity and stimulus complexity as well as their value. While task and stimulus complexity were similar between the groups, the value or importance of the stimuli may have differed. It is possible that low-dominant individuals attributed higher stimulus value, leading to larger P3b amplitudes [64]. This suggests that low-dominant individuals might be more inclined to interpret and process information meaningfully compared to high-dominant individuals.

These results imply that stimulus detection and processing may hold greater importance for low-dominant individuals, possibly due to social factors. For instance, individuals' memory performance and test scores are often evaluated by others, which may be more consequential for low-dominant individuals. On the other hand, the lower stimulus value for high-dominant individuals could indicate

that they are less concerned about others' opinions of their performance. This aligns with leadership research, which suggests that high-dominant individuals tend to be more self-centered and less receptive to others' opinions [65,66].

Furthermore, our findings are consistent with research highlighting the role of social factors in WM. Studies have demonstrated that social evaluation threat (SET), characterized by judgment and criticism from others, can disrupt WM performance and modulate activity in brain regions associated with WM (e.g., dorsolateral prefrontal cortex or DLPFC and intraparietal sulcus or IPS) [67]. The IPS-DLPFC circuit, crucial for WM performance, competes with the IPS to ventromedial prefrontal cortex (or IPS-VMPFC) circuit involved in SET processing, ultimately leading to WM performance decline. Similarly, stereotype threat has also been shown to impact WM capacity negatively [68].

4.3. ERP findings and gender differences

When discussing the topic of gender in relation to the current study, it is crucial to emphasize that the participants were carefully matched and grouped based on their gender. This measure was taken to ensure potential effects or differences attributed to gender were accounted for. Further, we were able to essentially minimize the impact of gender on the observed results by treating gender as a covariate in the statistical analysis. Therefore, by matching groups based on gender and accounting for it as a covariate in the analyses, the study aimed to ensure that observed between-group disparities in P3b amplitudes were not solely due to gender variations, but rather potentially linked to dominance. However, we observed within-group differences within low-dominance group where females indicated lower amplitudes of P3b. These findings raise intriguing questions about the understanding of dominance in women. It is crucial to address this issue since previous studies have predominantly focused on investigating dominance exclusively in men, perpetuating the belief that it is a trait primarily exhibited by men. The limited evidence available on the effects of dominance on women in both human and animal research indicates a gap in the existing literature on dominance which should be addressed in future studies.

4.4. ERSP findings

Aside from ERP results, the ERSP analysis consistently shows a significant increase in theta and beta ERS in the frontal and parietal regions of individuals with high dominance during the encoding and retrieval phases, throughout the duration of the P3b component. Generally, prior research literature suggests that an increased ERS of theta (almost always) and, in some cases, beta is associated with higher cognitive load and task difficulty [36–38,69–75]. These changes in the theta and beta bands result in a decreased amplitude of the P3b [39]. Our findings demonstrate a frequency shift during the P3b time course, where an increase in theta band is followed by an increase in beta activity. This kind of frequency shift from slow toward fast waves is associated with decrease in amplitude of ERP within the same time range. Considering that beta and gamma are associated with attentional resource allocation [76,77], it can be suggested that high-dominant individuals may allocate higher attentional resources, leading to a lower amplitude of the P3b and lower task difficulty in WM performance. Hence, our ERSP results, indicating higher ERS in high-dominant individuals, support the idea of their superior WM performance.

Further, during the encoding phase, the results indicate that there is a significant event-related synchronization (ERS) in both theta and beta bands in the high-dominance group compared to the low-dominance group. This suggests that during the process of encoding information into working memory, the high-dominance group exhibits higher activity in both theta and beta waves in frontal and parietal regions. This could indicate that the high-dominance group is more efficient in switching between different pieces of information held in WM, as indexed by beta waves [29,30].

In terms of theta waves, the higher synchronization in the high-dominance group suggests that they are better at guiding the brain in reinforcing correct associations and weakening incorrect ones during memory formation. The high-dominance group seems to have an advantage and more efficiency in the communication between the hippocampus and PFC as indexed via theta oscillations [31,35].

During the retrieval phase, the results could indicate that the high-dominance group may have improved memory access and higher efficiency compared to the low-dominance group. The higher synchronization in both theta and beta bands in frontal and parietal regions during the time course of the P3b ERP component (usually associated with attention and memory processing) suggests that the high-dominance group is more efficient in accessing and retrieving information stored in WM.

Overall, these results suggest that theta and beta waves play a crucial role in both encoding and retrieval phases, with the high-dominance group showing higher synchronization in these frequency bands during memory processes.

4.5. Correlations among behavioral and electrophysiological measures

Moving to discuss the association of different behavioral and electrophysiological measures, in this study, there was indeed a tradeoff between accuracy and RT. Our findings indicated that higher accuracy was typically associated with faster RT. This tradeoff suggests that participants who performed more accurately also tended to respond more quickly. However, it is important to note that the correlation between behavioral measures and ERP P3b amplitudes was not observed.

It is worth considering that the lack of significant correlation across all 3 electrodes suggests that the P3b amplitude may be linked to another component of WM that was not captured by the behavioral paradigm we employed. This aligns with a recent study featuring a large sample, which demonstrated that the amplitude of P3b is not significantly related to accuracy and RT of WM tasks. However, intriguingly, it can predict executive functions such as task switching and shifting [78]. Thus, it is possible that higher P3b amplitude of low-dominants in our study is linked to other factors such as executive functions or memory consolidation process during delay period

rather than intended encoding and retrieval processes of WM. Since our WM task specifically focused on P3b during the encoding and retrieval [23], we did not examine other components of WM such as consolidation during the delay period or executive functions. Consequently, we acknowledge that our experimental paradigm may not be suitable for addressing this question. Nevertheless, this is an intriguing question that could be examined in future studies.

Likewise, it can be argued that differences related to merely dominance trait contribute to the P3b differences rather than WM components. This way, it can be concluded that P3b can serve as a general index for dominance trait. The precision of this interpretation raises interesting and open questions for future research. However, it should be noted that this interpretation can be challenged by rich literature on the relationship of P3b and WM as summarized in the introduction section. To conclude, additional research is needed to investigate the potential relationship between P3b amplitude and executive functions, as well as other components of WM, across different dominance levels along with the possibility of P3b to serve as an electrophysiological index of social dominance to gain a more comprehensive understanding of this phenomenon.

Finally, there is a significant positive correlation between P3b amplitudes during the encoding and retrieval phases across all electrodes. Interpretation of this is based on the understanding of cognitive processes involved in memory encoding and retrieval. Generally, individuals who invest higher cognitive resources during encoding are likely to have better encoding and stronger memory traces. Our results imply that participants who invest more cognitive resources during encoding also do so during retrieval. This indicates that investing more cognitive resources during encoding not only does not reduce the need for such resources during retrieval but also more resource allocation is needed, as memory traces formed during encoding still require cognitive resources during retrieval to be accessed and retrieved successfully. This is also supported by previous research demonstrating that memory encoding and retrieval involve common neural networks and cognitive processes, such as increased activity in hippocampus and frontal regions [79]. Such efforts in the allocation of attentional and memory resources to accomplish short-term remembering and information manipulating are needed among both low- and high-dominants since they both have higher P3b amplitudes during the retrieval than the encoding information.

5. Conclusion

In conclusion, our study provides the first evidence of differences in neural measures of WM between individuals with high and low social dominance. These findings have both theoretical and practical implications. Real-life environments, such as schools and workplaces, often have stable social hierarchies where individuals must navigate and work under the guidance of high-ranking leaders. Understanding the WM capabilities of individuals with different levels of social dominance can inform the design of educational and organizational settings. This is particularly important considering that dominance is a crucial trait in predicting future leaders. Overall, our study opens up avenues for further exploration and understanding of the interplay between social dominance, cognitive processes, and neural mechanisms. By addressing the limitations and incorporating more robust methodologies, future research can provide deeper insights into the intricate relationship between social factors and cognitive functioning.

This study highlights the interplay between social, interpersonal factors and cognitive, neural processes. This aligns with the scope of social cognitive neuroscience, which integrates various levels of organization and analysis. By investigating the impact of social dominance on WM, we contribute to a broader understanding of the complex interactions between social factors and cognitive functioning. However, several limitations of our research should be acknowledged.

First, the use of questionnaires to assess social dominance may be limited in terms of their validity. Self-report measures rely on the assumption that participants are honest in their responses, despite potential biases such as motivation or social desirability. To overcome this limitation, future studies could employ experimental tasks to manipulate participants' social rank while simultaneously recording neural responses.

Second, our strategy for creating groups was limited by the nature of our sample. We were unable to separate high and low dominance groups using the highest and lowest percentiles, as we relied on voluntary participation. This may have introduced some selection bias. Future research could aim to recruit participants that cover the entire spectrum of social dominance to ensure a more comprehensive representation of the trait.

Third, while our study utilized EEG/ERP to investigate the relationship between social dominance and WM, the neural mechanisms underlying this relationship remain unclear. EEG/ERP has limited spatial resolution, making it challenging to understand the precise neural pathways and networks involved. To address this limitation, future research should consider employing neuroimaging methods, such as fMRI or fNIRS, to elucidate the neural mechanisms underlying the association between social dominance and WM.

Lastly, due to potential confounding variables such as fatigue and order effect, we encountered difficulty in including an additional task to assess WM capacity among high- and low-dominant groups. Therefore, it is suggested that future research explore this topic by incorporating a different task to corroborate and authenticate our results. Additionally, we were unable to thoroughly examine other potential contributing factors such as shifting, switching, and consolidation processes that may influence the present findings. As a result, it is suggested that future research investigate these aspects utilizing more meticulous paradigms and methodologies.

Declaration of generative AI in scientific writing

We acknowledge the use of ChatGPT to correct grammatical errors, edit, and improve English writing.

Data availability

Data will be made available upon reasonable request from the corresponding author.

Ethics and consent statements

This study was conducted in conformity with the Declaration of Helsinki and has been approved by the local ethics committee (IR.TABRIZU.REC.1400.014).

The disclosure of data collection and analysis

We declare that we reported all measures, conditions, and data exclusion in the paper.

CRediT authorship contribution statement

Hadi Mohamadpour: Investigation, Methodology, Data analysis, Visualization, Software, Data curation, Writing – original draft, Writing – review & editing. **Farhad Farkhondeh Tale Navi:** Visualization, Data analysis, Writing – review & editing. **Soomaayeh Heysiattalab:** Conceptualization, Methodology, Supervision, Validation, Funding acquisition, Writing – review & editing. **Metehan Irak:** Methodology, Writing – review & editing. **Abdol-Hossein Vahabie:** Data analysis, Writing – review & editing. **Behzad Nikzad:** Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.heliyon.2024.e37389>.

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