

Neural correlates of cognitive processing capacity in elite soccer players

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ABSTRACT

Although great progress has been made in our understanding of perceptual-cognitive expertise in team sports, the neurocognitive mechanisms underlying such cognitive advantage in the face of multiple, sometimes conflicting, channels of information are not well understood. Two electroencephalographic indices associated with perceptual decisions, the P3 component of event-related potential and alpha inter-trial phase coherence (ITPC), were measured and compared across elite soccer players and non-athletic controls while performing a redundant-target task. Specifically, we adopted an effective diagnostic tool, Systems Factorial Technology, to assess participants' workload capacity. Soccer players exhibited larger workload capacity while making faster decisions compared with controls. Moreover, this larger workload capacity was associated with modulations of P3 and alpha ITPC when processing two targets relative to one target and one distractor, an effect that was not observed in controls. Together, the present findings offer a possible mechanistic explanation of perceptual-cognitive expertise in the context of team sports.

1. Introduction

The human brain is a rapidly adapting, dynamically changing system that allows learning from new experiences, inducing alterations in brain function and structure, a process called neuroplasticity (Dayan & Cohen, 2011). Extensive evidence has demonstrated neuroplastic changes following motor training (Draganski et al., 2004; Moreau, Morrison, & Conway, 2015). As such, expertise in the motor domain (e.g., sport) has been proposed as a promising framework to understand training-related neuroplastic changes (Bezzola, Mérillat, Gaser, & Jäncke, 2011; Bianco, Berchicci, Perri, Quinzi, & Di Russo, 2017; Rosenkranz, Williamon, & Rothwell, 2007; Wang, Yang, Moreau, & Muggleton, 2017). In particular, team or strategic sports such as soccer, which require processing and integration of multiple signals (e.g., ball, teammates, goal, and opponents) (Singer, 2000), can provide a valuable framework to understand the cognitive and neural correlates associated with sport-induced neuroplasticity (Scharfen & Memmert, 2019; Ward & Williams, 2003; Yao et al., 2020). While there is increasing evidence demonstrating cognitive advantages in high-performing team sports players, little is known about how their neurocognitive systems process

and integrate multiple signals for decision-making.

Imagine that you are one of the players during a soccer game. The game environment may consist of a variety of information (e.g., the positions of the teammates and opponents) to drive you to make decisions (e.g., pass, dribble, or shoot). Upon detection of any signals for moving forward into attack, you must respond immediately by making an appropriate decision (e.g., pass or dribble). Certainly, a quick response is a vital factor for successful performance in sports. Surprisingly, although there has been a plethora of research demonstrating that athletes outperformed non-athletes on measures of attention and cognitive processing speed (Chaddock, Neider, Voss, Gaspar, & Kramer, 2011; Hung, Spalding, Santa Maria, & Hatfield, 2004; Wang et al., 2013), no conclusive evidence exists to support the processing speed advantage in team sports players (Alves et al., 2013; Memmert, Simons, & Grimme, 2009; Pesce, Tessitore, Casella, Pirritano, & Capranica, 2007; Verburgh, Scherder, van Lange, & Oosterlaan, 2014; Voss, Kramer, Basak, Prakash, & Roberts, 2010; Wylie et al., 2018). It could be possible that the general speed of cognitive processing might not be sufficiently sensitive to probe the relevance of the specific cognitive profile of team sports, which could even paradoxically call into question

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the ecological utility of laboratory measures of cognitive functioning in this type of sport (e.g., talent identification) (Beavan, Chin et al., 2020, Beavan, Spielmann et al., 2020).

On the other hand, many team sports situations necessitate perceiving two or more signals simultaneously (e.g., perceiving the positions of teammates and the opponents while controlling the ball), resulting in increased workload on the processing system. As a consequence, players must operate in a high-workload environment that forces them to divide attention across multiple information sources, and sometimes are confronted with sources providing conflicting information. An ecologically valid example is that a dribbling player has to inhibit passing a ball when detecting a teammate on the offside position, despite other cues (e.g., hand gesture and voice) signaling to pass. One interesting question is how the increased workload affects a player's efficiency in making decisions. Note that an increase in workload (i.e., the number of to-be-processed signals) may facilitate or impair performance, depending on the capacity of the processing system (Townsend & Eidels, 2011). Although there has been some studies showing that team sports players exhibited advantages in executive functions (Krenn, Finkenzeller, Würth, & Amesberger, 2018; Meng, Yao, Chang, & Chen, 2019; Wylie et al., 2018), a type of high-order cognitive processes that are crucial for decision-making (Diamond, 2013; Friedman & Miyake, 2017), it remains to be determined whether such cognitive superiority is associated with more efficient multi-signal information processing.

To address this issue, we adopted a redundant-target task, which mimics the demands of a high-workload environment. The redundant-target task has been commonly used to evaluate an individual's capacity of simultaneously monitoring multiple sources of information (Little, Eidels, Fifić, & Wang, 2018; Townsend & Eidels, 2011). In such tasks, the participants are required to make a positive response when one or more operationally-defined targets are present, and a target-absent response is made when no targets are detected. Here, we employed a color-shape redundant-target task (Chang & Yang, 2014; Yang et al., 2019), where the test display consisted of two targets (redundant-target trial, C + S+), one target and one distractor (single-target trial, C + S- or C-S+), or two distractors (no-target trial, C-S-)¹. The typical finding in this paradigm is that mean reaction times (RTs) to redundant targets are found to be shorter than mean RTs to single targets, and this RT advantage with redundant targets is known as a redundancy gain (RG) or redundant-target effect (Miller, 1982). The RG may have occurred because of the statistical facilitation effect (Raab, 1962) or coactivation from parallel channels (Miller, 1982). As such, by comparing the RTs of the redundant-target trials to the single-target trials, we can investigate the variation of the processing efficiency as an increase in workload, known as the measure of workload capacity (Miller, 1982). With regard to its ecological pertinence, the assessment of workload capacity has been widely applied to explore the individual differences in information processing mechanisms, such as working memory capacity, cognitive aging, and personality traits (Ben-David, Eidels, & Donkin, 2014; Chang & Yang, 2014; Yang et al., 2019; Yu, Chang & Yang, 2014), demonstrating its utility in the investigation of individual differences in cognitive processing capacity.

Although it is common to use mean RT analysis to draw conclusions about the individual differences in prior sport literature, we cannot make strong inferences about the processing differences based on this measure alone. For example, serial processing and parallel processing may mimic each other when solely considering mean RTs, which is known as the problem of model mimicry (Townsend & Wenger, 2004). Thus, we introduced the Systems Factorial Technology (SFT, Little, Altieri, Fifić, & Yang, 2017; Townsend & Nozawa, 1995) to the present study. SFT is a useful and diagnostic mathematical tool to study the properties of perceptual and cognitive mechanisms underlying

decision-making, including the mental architecture (i.e., the order of multiple-signal processing), stopping rule (i.e., the amount of information required for devious decision-making) and workload capacity (i.e., the variation of processing efficiency as a function of workload). Here, we primarily focus on the workload capacity analysis to emulate the real-world situation where people need to handle multiple sources of information simultaneously. Taking advantage of workload capacity analysis via SFT, we can better understand how efficiency of information processing during decision-making may change as a function of workload, and thus the possible perceptual and cognitive processing mechanisms underlying individual differences (e.g., independent/interactive parallel/serial system). To elaborate, an unlimited-capacity system indicates that increasing workload does not affect the individual channel processing speed. On the other hand, a supercapacity or limited-capacity system indicates that increasing workload may speed up or slow down the individual channel processing speed. Although workload capacity and mental architecture are theoretically distinct constructs, it is traditionally assumed that a certain type of architecture may possess a certain range of capacity. For example, a standard serial system is of limited capacity. A standard parallel system is of unlimited capacity. A coactive system is of supercapacity. Eidels, Houpt, Altieri, Pei, and Townsend (2011) further demonstrated that a parallel system possessing a certain level of interaction may result in different levels of capacity. That is, parallel processing with facilitatory inter-channel interaction would result in supercapacity processing whereas parallel processing with inhibitory inter-channel interaction would result in limited-capacity processing.

The traditional workload capacity analysis of SFT framework can deal with multiple-signal processing in which both channels contain the targets, yet it cannot be applied to situations where multiple channels exhibit conflicting information. As a result, instead of the traditional workload capacity analysis, we adopted a novel capacity measure, so-called resilience capacity, which was recently developed by Little, Eidels, Fifić, and Wang (2015). The resilience capacity is operationally defined as the comparison of the processing efficiency when redundant targets are present to the unlimited-capacity, independent, parallel model baseline (UCIP). The UCIP baseline is predicted from the two single-target conditions where a target is presented against a distractor. The resilience capacity is expressed as:

$$R(t) = \frac{H_{c+s+}(t)}{H_{c+s-}(t) + H_{c-s+}(t)} \quad (1)$$

where $H_{c+s}(t)$, $H_{c+s}(t)$, and $H_{c-s}(t)$ denote the integrated hazard functions of the redundant-target conditions and two single-target conditions, respectively. When $R(t) > 1$, it indicates supercapacity processing; when $R(t) = 1$, it indicates unlimited-capacity processing; when $R(t) < 1$, it indicates limited-capacity processing. When processing is of unlimited capacity, it implies that the individual channel processing efficiency does not change even when an additional target or a distractor is added to the processing system. In other words, individual channel processing is resilient to additional channel processing. Super-capacity individuals can take advantage of the redundant-target signal processing to boost processing efficiency, via a facilitatory inter-channel interaction². By contrast, when processing is of limited capacity, redundancy may slow down the information processing speed, in the form of inhibitory inter-channel interaction. Therefore, we can utilize the resilience capacity analysis to make inference about how an information-processing system deals with multiple sources that may provide conflicting information for decisions.

¹ Note that C stands for color, S stands for shape, + denotes target-present, and - denotes distractor-present.

² It is notable that supercapacity may have also occurred because distractor processing slows down the single-target processing, which results in an increase in the workload capacity. We will discuss about this possibility in the general discussion.

In order to investigate how the neural system may respond to variations in the number of information sources during perceptual decisions, we measured the well-known electroencephalographic (EEG) and event-related potential (ERP) signatures of target detection process during perceptual decisions: alpha phase (Busch, Dubois, & VanRullen, 2009; Hanslmayr et al., 2005) and P3 (Nieuwenhuis, Aston-Jones, & Cohen, 2005; Twomey, Murphy, Kelly, & O'Connell, 2015). A large number of studies have used P3 to explore the perceptual-cognitive expertise in many different kinds of sports (Memmert, 2009). In terms of team sports, albeit limited, research has demonstrated differential modulations of P3 during perceptual decisions between elite athletes and their sub-elite or non-athletic counterparts (Iwadate, Mori, Ashizuka, Takayose, & Ozawa, 2005; Radlo, Janelle, Barba, & Frehlich, 2001). Despite limited evidence regarding oscillatory alpha phase in athletes, investigating of both indices can provide complementary information into the underlying neural mechanisms, given the functional similarity between P3 and alpha phase during target detection process (Yordanova & Kolev, 1998). For example, although ERP has the capacity to capture the temporal dynamic of the neuroelectric mechanisms underlying cognitive functioning, some considerable functional significance contained in the EEG frequency dynamics may be lost as a consequence of the time-domain averaging (Makeig, Debener, Onton, & Delorme, 2004). Accordingly, investigating both EEG and ERP can provide deeper insight into the perceptual-cognitive expertise in sports (Nakata, Yoshie, Miura, & Kudo, 2010; Park, Fairweather, & Donaldson, 2015; Wang, Moreau, & Kao, 2019).

The aim of this study was to investigate whether the perceptual-cognitive expertise in team sports is related to efficient process and integration of multiple sources of information. To the best of our knowledge, no prior study has used workload capacity measures to infer the dynamic process of perceptual decision-making in team sports players. We asked the following questions: if team sports expertise is related to individual difference in workload capacity, to what extent does it differ between elite athletes and a non-athletic cohort, and could potential differences be explained by the cognitively-induced neural modulations? The study was designed to provide important insight into the nature of information processing capacity associated with team sports expertise and its underlying mechanisms.

2. Materials and methods

2.1. Participants

Sixty subjects, 30 male Division I collegiate soccer players (age: 20.10 ± 0.92 years; education: 14.10 ± 0.92 years, professional training experience: 11.31 ± 2.09 years) and 30 physically active male non-player novices from general student population (age: 21.73 ± 1.43 years; education: 15.30 ± 0.91 years) participated in the experiment. All of the soccer players were active team members of a collegiate soccer team and were engaged in a regular training program at the time of the study. Controls reported spending at least three times per week doing physical exercise but had no historical specialization in any sport. Notably, in order to avoid any influence of gender-sport interactions on cognitive function (Alves et al., 2013; Voss, Kramer, Basak, Prakash, & Roberts, 2010), we only recruited male participants. No individuals reported a history of neurological problems or cardiovascular diseases, nor were any taking medications known to affect cognitive function. Informed consent was obtained from all participants prior to the study, and approval was obtained from the Human Research Ethics Committee (HREC) of National Cheng Kung University. In accordance with guidelines of the HREC, the data acquired in the present study cannot be shared with researcher without the written re-consent of the participants.

2.2. Tasks and measures

2.2.1. Redundant-target task

This study adopted the same redundant-target task as prior studies in our group (Chang & Yang, 2014; Yang et al., 2019; Yu, Chang, & Yang, 2014), and was programmed with E-prime 2.0 (Psychology Software Tools, Inc, Sharpsburg, PA). All soccer players were tested on days without training to prevent potential fatigue effects induced by physical training on task performance (Alves et al., 2013; Wang et al., 2017). In addition, experimenters ensured that all participants had not engaged in any specific activity prior to cognitive testing known to bias the effects of interest (e.g., exercising or drinking alcohol).

In the redundant-target task, the test display consisted of a letter that was either an O or an X, either green or cyan, 1° (horizontal) \times 1° (vertical) presented at the center of the screen. The target shape was defined as X and the target color was defined as green. The distractor shape was defined as O and the distractor color was defined as cyan. There were four types of test displays: both target features were presented (i.e., redundant-target trial: a green X); a single target feature and a distracting feature were presented simultaneously (i.e., single-target trial: a green O or a cyan X); or neither target features were presented (i.e., no-target trials: a cyan O) (Fig. 1a). Each condition was equally distributed and was randomly intermixed within each block such that the participants would not be able to anticipate the presence of redundant-target trials. There were 20 practice trials and four blocks of 100 formal test trials, yielding 400 formal test trials in total.

All participants performed the task with concomitant EEG recording (see procedure below). The experiment was conducted in a dimly lit and soundproof room in and the participants sat in front of a screen at a viewing distance of 100 cm. All the visual stimuli were presented against a black background on a 21-inch cathode-ray tube (CRT) display. A trial began with a 1000 ms fixation cross ($0.5^\circ \times 0.5^\circ$). Afterwards, a central colored letter was presented until the participant made a response or 2000 ms had elapsed. Then, a central fixation cross ($0.5^\circ \times 0.5^\circ$) appeared for a duration ranging from 1500 ms to 2000 ms, regarded as the inter-trial interval (ITI) (Fig. 1b). Participants were instructed to press the “/” key as quickly and accurately as possible when they detected one of the target features (either color green or shape X); otherwise, they were instructed to hold their responses when neither target features were detected.

2.2.2. EEG acquisition

The EEG recording procedure was performed in a manner similar to previous studies in our groups (Wang et al., 2017). EEG activity was recorded using a Nu-Amps EEG amplifier and the Scan 4.3 package (Neuroscan Inc., El Paso, TX, USA) with 32 electrodes mounted in an elastic cap (Quik-Cap; Compumedics, Neuroscan Inc.) designed for the International 10–20 System. The left and right mastoids were used as online references and a ground electrode was placed on the mid-forehead on the Quik-Cap. In addition, two sets of bipolar electrodes were placed on the upper and lower sides of the left eye, and on the canthi of both eyes in order to monitor vertical (VEOG) and horizontal (HEOG) eye-movements. Electrode impedances were kept below 10k Ω . EEG data were acquired with an analogue–digital rate of 1000 Hz per channel, filtered with a Butterworth bandpass filter (0.1–70 Hz), a 60-Hz notch filter, and written continuously onto a hard disk for subsequent offline analysis.

2.3. Data reduction and statistical analyses

2.3.1. Behavioral data

E-prime 2.0 was used to record behavioral performance in terms of RTs (in milliseconds) and accuracy. RTs were excluded from analysis if they were from: (1) non-response trials, (2) error trials, and (3) correct trials with latencies more than two standard deviations above the mean.

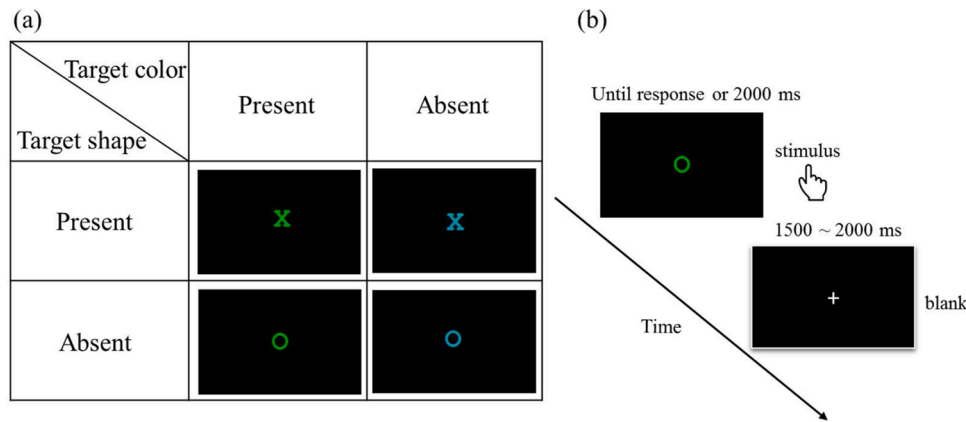


Fig. 1. (a) Illustration of all possible test conditions. (b) Illustration of the experimental procedure of the redundant-target detection task.

2.3.2. SFT and workload capacity

According to SFT, the capacity coefficient $C(t)$ was computed to infer an individual's workload capacity (Townsend & Eidels, 2011; Townsend & Nozawa, 1995). Notably, because in the present case the single-target trial consists of the distracting information, we used a modified capacity coefficient, i.e., resilience coefficient $R(t)$, to estimate the workload capacity (Little et al., 2015; Yang et al., 2019). $R(t)$ was computed according to the Eq. (1). The ranges of values of $R(t)$ and their implications are as follows: (1) a value of $R(t) > 1$ suggests the system is of super-capacity: increasing the workload speeds up the processing speed for an individual channel; (2) a value of $R(t) = 1$ suggests the system is of unlimited capacity: the change in workload does not affect the processing efficiency of an individual channel; (3) a value of $R(t) < 1$ suggests the system is of limited capacity: increasing the workload slows down the processing speed for an individual channel.

2.3.3. Functional principal component analysis of the resilience function

We further employed functional principal components analysis (fPCA) with varimax rotation to decompose $R(t)$ coefficient function into several principal components (Burns, Houpt, Townsend, & Endres, 2013). fPCA is a structural extension of standard PCA (Ramsay & Silverman, 2005) and can be used to describe the entire functions using a small number of scalar values (i.e., the loading of the principal component) (Burns et al., 2013). This approach enables us to describe which part of the function-level property is crucial for distinguishing the effect of expertise on the workload capacity as a function of RT. In particular, it has been suggested that fPCA has the capacity to provide comprehensive information about the resilience function, particularly for the individual differences (Houpt & Little, 2017). Thus, we can conduct the statistical analysis of the resilience function via fPCA to discover the capacity differences in multi-signal information processing across soccer players and controls.

2.3.4. Event-related potentials data processing

Offline ocular-corrected EEG was first segmented into epochs ranging from -100 ms to 800 ms relative to target onset. The EEG data were then filtered with a digital band-pass of 0.1 and 30 Hz (12 dB/octave) with FIR filter. The FIR filter was adopted because it can achieve linear phase response (Kiebel, Tallon-Baudry, & Friston, 2005). The 100 ms pre-target period was used for baseline correction. Data with behavioral errors or artifacts with amplitudes $\pm 100\mu\text{V}$ in the HEOG channel and the other channels were discarded. The rest of the resulting artifact-free data was then averaged according to each condition. We examined the P3 component from electrodes adjacent to midline areas (i.e., Fz, Cz, Pz) (Yordanova & Kolev, 1998; Yordanova, Kolev, & Polich, 2001). On the basis of visual inspection of the grand average ERPs (Fig. 5), the mean amplitude and peak latency of P3 for each condition were determined for each participant. P3 was defined as the most

positive deflection in a time window between 300 and 600 ms post-stimulus. The mean amplitudes for the P3 were defined as the mean areas during the time window of peak latency ± 25 ms.

2.3.5. Time-frequency analysis of EEG

The EEG analysis was performed using SPM8 for MEG/EEG (www.ion.ucl.ac.uk/spm/) and custom Matlab (MathWorks) scripts (Hsu, Tseng, Liang, Cheng, & Juan, 2014; Wang, Liang, & Moreau, 2020). Only data collected from correct trials was analyzed. Prior to the time-frequency analysis, we identified large artifacts in the continuous EEG data and set the maximum level for eye-blinks. A correction for eye-blinks was applied to the EEG data, with eye-blink peaks being derived from VEOG by means of regression and correlation and these data used to perform eye movement correction for all electrodes. Continuous EEG data were locked to the target onset and were segmented into epochs from -1500 to 1500 ms relative to this time point. Trials containing artifacts with amplitudes exceeding $\pm 150\mu\text{V}$ were discarded. Inter-trial phase coherence (or phase-locking index) estimates were computed by a continuous Morlet wavelet transform (Morlet wavelet factor = 6) of single-trial data for the frequency band ranging from 2 to 30 Hz (Roach & Mathalon, 2008). ITPC measures the temporal consistency of the phase value for a given frequency band at a certain time point. Phase coherence varies from 0 to 1, where 0 indicates absence of any EEG phase consistency across trials, and 1 indicates identical EEG phase consistency across trials (Delorme & Makeig, 2004). In line with the ERP analysis, the electrodes around midline regions (Fz, Cz, Pz) were clustered here for calculating the ITPC values (Yordanova & Kolev, 1998). We specifically focused on alpha activity (i.e., 9–13 Hz) due to the evidence that greater alpha phase resetting has been associated with better perceptual decision making (Busch et al., 2009; Hanslmayr et al., 2005). The ITPC values for each time-point and frequency were used as the measures of interest for statistical analysis.

2.3.6. Behavior-EEG correlations

Correlations between behavioral and EEG data were examined to gain insight into the mechanisms that may underlie the individual differences in workload capacity across the two groups. Behavioral data included RG of mean RTs and fPCA components of $R(t)$. ERP data consisted of the mean amplitudes and peak latencies of the P3 components acquired from difference waveforms for redundant-target and single-target trials across the electrodes of interest (Fz, Cz, Pz). For time-frequency of EEG data, we correlated all the bins contrasting redundant-target and single-target trials in the time-frequency representation with all of the behavioral indexes.

2.3.7. Statistical analyses

This study employed both frequentist (in SPSS 18.0) and Bayesian hypothesis testing (RRID: SCR_001905; R Core Team, 2018) for analyses

of behavioral and ERP data. This framework allows quantifying evidence across a range of hypotheses, including the null. In line with previous studies in the field (Moreau, Kirk, & Waldie, 2017; Wang, Moreau, Yang, Tsai et al., 2019), all priors used in our analyses were the default scales (Morey & Rouder, 2015). Typically, a Bayes Factor (BF) greater than 3 is considered moderate evidence in favor of the hypothesis tested (i.e., the null or the alternative), whereas a BF between 1 and 3 suggests the data are inconclusive (Dienes, 2014). All analyses were set to 10^4 iterations, with diagnostic checks for convergence. One chain per analysis was used for all analyses reported in the paper, with a thinning interval of 1 (i.e., no iteration was discarded).

Bayesian independent samples *t*-tests with a Cauchy prior scale of 0.707 and independent samples *t*-tests were used to examine the group differences in demographics, RG of mean RTs, and each fPCA component of $R(t)$. A Bayesian Contingency Tables test and a *Chi-Square* test were used to test the difference in the number of individuals classified as supercapacity or non-supercapacity between groups. Bayesian mixed-design ANOVAs with default prior scales and mixed-design ANOVAs were conducted to analyze the accuracy performance, the mean RTs, the amplitudes, and the latencies of P3. For the time-frequency analysis of EEG, we used SPM8 for MEG/EEG (www.fil.ion.ucl.ac.uk/spm/) with custom Matlab scripts (Liang et al., 2014; Wang et al., 2017) to test the *condition* effect (redundant-target, single-target; paired *t*-tests) and *group* effect (soccer players, controls; independent *t*-tests), with a false discovery rate (FDR) correction (Benjamini & Yekutieli, 2001) for multiple comparisons. Finally, the Pearson correlation tests with FDR correction for multiple comparisons and Bayesian correlation tests with Jeffrey's prior (Ly, Verhagen, & Wagenmakers, 2016) were used to assess the association between the EEG (P3 and alpha phase) and behavioral measurements of processing capacity [RG of mean RTs and fPCA components]. All tests for significance were set at alpha level 0.05.

3. Results

3.1. Participant demographics

Demographic variables including height (soccer players: 173.47 ± 6.84 cm vs. controls: 172.93 ± 4.88 cm; $BF_{10} = 0.276$; $t(58) = .35$, $p = 0.730$), weight (soccer players: 66.80 ± 6.67 kg vs. controls: 64.37 ± 6.74 kg; $BF_{10} = 0.599$; $t(58) = 1.41$, $p = 0.165$), and body mass index (BMI) (soccer players: 22.20 ± 1.75 vs. controls: 21.50 ± 1.78 ; $BF_{10} = 0.690$; $t(58) = 1.52$, $p = 0.133$) did not meaningfully differ between soccer players and controls.

3.2. Mean behavioral performance

Table 1 shows accuracy and mean RTs of correct trials across groups and conditions.

3.2.1. Accuracy

The results showed very strong support for the main effect of

Table 1

Behavioral performance of the redundant-target detection task for soccer players and controls.

Group	Accuracy (%)			Reaction time (msec)		
	RT	ST	NT	RT	ST	RG
Soccer Players (n = 30)	99.93	99.33	93.97	428.60	484.82	56.22
Controls (n = 30)	99.97	99.32	92.10	426.70	479.46	56.86

Note: "RT", "ST", and "NT" represent the redundant-target, single-target, and no-target conditions, respectively. Redundancy gain (RG) is defined as the difference in mean reaction times between the redundant-target and single-target conditions. Note that mean reaction time of the no-target condition was not shown because any response in this condition is incorrect for the Go/No-go version of the redundant-target detection task.

condition [$BF_{10} = 7.56e+29$; Greenhouse-Geisser corrected: $F(1.04, 60.33) = 105.02$, $p < .001$, $\eta_p^2 = .64$], with higher accuracy in the redundant-target condition (99.95 ± 0.22 %), intermediate accuracy in the single-target condition (99.33 ± 0.82 %), and lower accuracy for the no-target condition (92.73 ± 5.19 %) (all $BF_{10} > 318.95$ and $p < .001$). However, evidence for the main effect of *group* [$BF_{Inclusion} = 0.20$; $F(2, 116) = .89$, $p = .413$] and *group* \times *condition* interaction [$BF_{Inclusion} = 0.18$; $F(2, 116) = .89$, $p = .413$] was extremely weak.

3.2.2. Mean RTs

The results showed very strong support for the main effect of *condition* [$BF_{10} = 3.49e+32$; $F(1, 28) = 5880.22$, $p < .001$], with faster RTs for redundant-target condition than the single-target condition, consistent with prior research showing the RG (Miller, 1982). However, evidence for the main effect of *group* [$BF_{Inclusion} = 0.55$; $F(1, 58) = .03$, $p = .854$] and *group* \times *condition* interaction [$BF_{Inclusion} = 0.38$; $F(1, 58) = .03$, $p = .854$] was extremely weak.

3.2.3. Redundancy gain (RG)

The *t*-tests revealed that there was no meaningful group difference in RG [$BF_{10} = 0.26$; $t(58) = .11$, $p = .914$].

3.3. Systems factorial technology and resilience

Fig. 2 plots the resilience capacity coefficient function for each group. From the visual inspection, the results showed that, for most participants in the soccer players, $R(t)$ was larger than 1 for the faster RTs, suggesting supercapacity processing. In contrast, for most participants in the controls, $R(t)$ was equal to or less than 1 for all times t and a few values of $R(t)$ were hovering around 0.5, suggesting unlimited-capacity to (very) limited-capacity processing. To confirm our observations, we conducted a non-parametric bootstrapping method to simulate 1000 samples for each condition and to construct the 95 % confidence interval for $R(t)$ for each individual (Van Zandt, 2000). If the 95 % confidence interval for $R(t)$ exceeds 1 at some time t , we infer that the participant adopts supercapacity processing; otherwise, we infer that the participant adopts non-supercapacity processing (unlimited-capacity or limited-capacity processing). Please see Chang and Yang (2014) and Yu et al. (2014) for more details about the data analysis.

Table 2 presents the classification results based on the non-parametric simulation. Results revealed that 14 out of 30 soccer players were categorized as supercapacity processing; in contrast, only 7 out of 30 controls were categorized as supercapacity processing. The statistical analyses showed marginal evidence for a difference in the number of individuals classified as supercapacity and non-supercapacity across groups ($BF_{10} = 1.712$; $\chi^2(1) = 3.59$, $p = .058$), indicating a trend showing that more soccer players exhibited supercapacity processing relative to the controls.

3.4. fPCA of the resilience function

We combined all the participants' data to estimate the mean resilience capacity function (Fig. 3a) and the mean centered capacity functions for each individual (Fig. 3b), allowing for the investigation of overall trend and variability across groups. Fig. 4a, known as the screen plot, shows the amount of variance accounted for by each eigenfunction, and the results suggested a two-component solution. Fig. 4b shows the component with the mean function on the left and relative to the mean on the right. The first principal function accounts for 42 % of the variance and indicates a general increase of the resilience function for the faster RTs. The second principal function explains 27 % of the variance and indicates that a change in the slope of the function, with a decrease in capacity for early times and an increase in capacity for the later responses. The *t*-tests revealed a clear evidence for group-level difference in factor score for the first component ($BF_{10} = 4.887$; $t(58) = 2.68$, $p = .010$), with higher factor score for the soccer players than for the

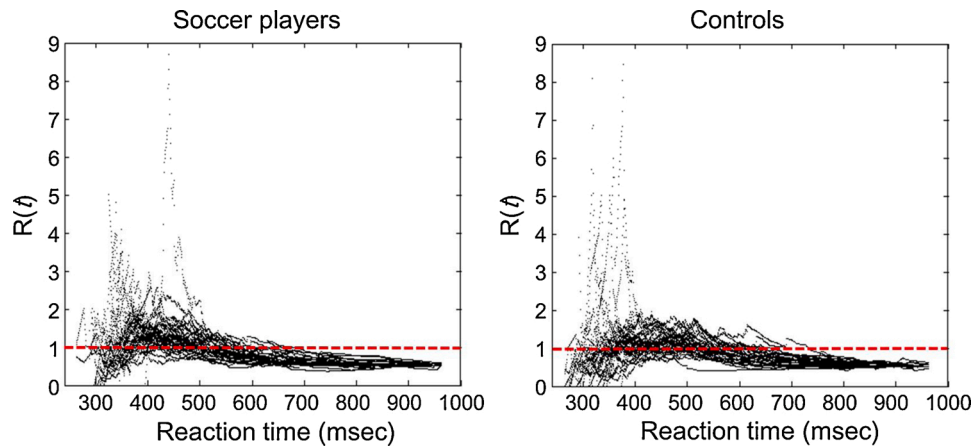


Fig. 2. Plots of the capacity coefficient $R(t)$ for the controls and soccer players in the redundant target task. $R(t)$ was calculated from each individual's empirical distribution of RTs.

Table 2

Contingencies for the capacity classification based on simulated data for each group.

Group	Supercapacity	Non-super capacity
Soccer players (n = 30)	14	16
Controls (n = 30)	7	23

controls (Fig. 4c, d). However, no meaningful group difference in factor score was found for the second principal component ($BF_{10} = 0.263$; $t(58) = -0.07$, $p = .947$) (Fig. 4c and d).

3.5. Event-related potential P3 component

The ERP dynamics of the P3 component across conditions in each group can be found in Fig. 5a.

3.5.1. P3 amplitude

We found support for the main effect of *electrode* [$BF_{\text{inclusion}} = 5.08e+11$; Greenhouse-Geisser corrected: $F(1.62, 94.00) = 30.52$, $p < 0.001$, $\eta_p^2 = .35$], with smaller P3 amplitude at Fz ($6.15 \pm 3.19\mu\text{V}$),

intermediate P3 amplitude at Cz ($7.26 \pm 3.25\mu\text{V}$), and greater P3 amplitude at Pz ($7.92 \pm 3.18\mu\text{V}$) (all $BF_{10} > 4.6$ and $p < .003$). Similarly, we found support for the main effect of *condition* [$BF_{\text{inclusion}} = 6.40e+12$; $F(1, 58) = 24.79$, $p < 0.001$, $\eta_p^2 = .30$], with the P3 amplitude greater in the redundant-target condition ($7.77 \pm 3.01\mu\text{V}$) than in the single-target condition ($6.46 \pm 3.44\mu\text{V}$). There was also strong evidence for the interaction *condition* \times *group* [$BF_{\text{inclusion}} = 6440.37$; $F(1, 58) = 9.67$, $p = 0.003$, $\eta_p^2 = .14$]. Decomposition of the interaction revealed support for the effect of *condition* for the soccer players (all $BF_{10} > 3$; $p < .001$) but not for controls (all $BF_{10} < 1$; $p = .162$) (Fig. 5b). We also tested additional models, for which we found no meaningful support: one with *group* only [$BF_{10} = 0.75$; $F(1, 58) = 2.00$, $p = 0.162$], the *electrode* \times *group* interaction [$BF_{\text{inclusion}} = 0.19$; $F(2, 116) = .51$, $p = 0.604$], the *condition* \times *electrode* interaction [$BF_{\text{inclusion}} = 0.15$; Greenhouse-Geisser corrected: $F(1.62, 94.79) = .298$, $p = 0.066$], and the *condition* \times *electrode* \times *group* interaction [$BF_{\text{inclusion}} = 0.01$; $F(2, 116) = .36$, $p = 0.589$].

3.5.2. P3 latency

We found support for the main effect of *electrode* [$BF_{\text{inclusion}} = 68.79$; Greenhouse-Geisser corrected: $F(1.64, 95.29) = 17.56$, $p < 0.001$, $\eta_p^2 = .23$], with shorter P3 latency at Pz (421.98 ± 37.25 ms) than at Fz (436.17 ± 39.63 ms) and Cz (434.46 ± 40.40 ms) (both $BF_{10} > 12.36$

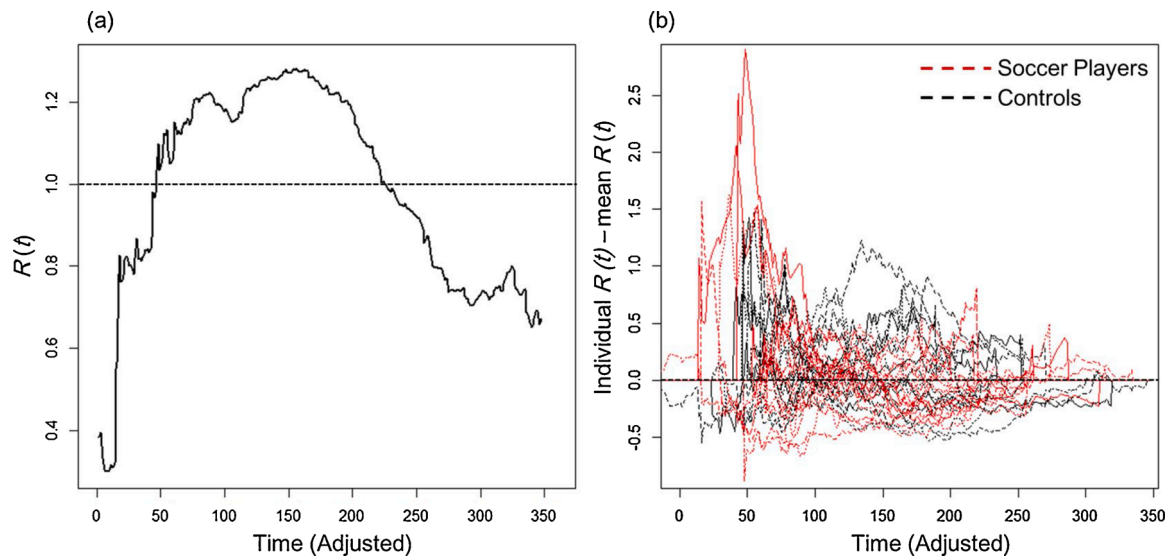


Fig. 3. (a) The mean capacity function, averaged across all participants. (b) The mean centered capacity functions for each individual and group. Red lines indicate the functions for soccer players and black lines indicate the functions for controls. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

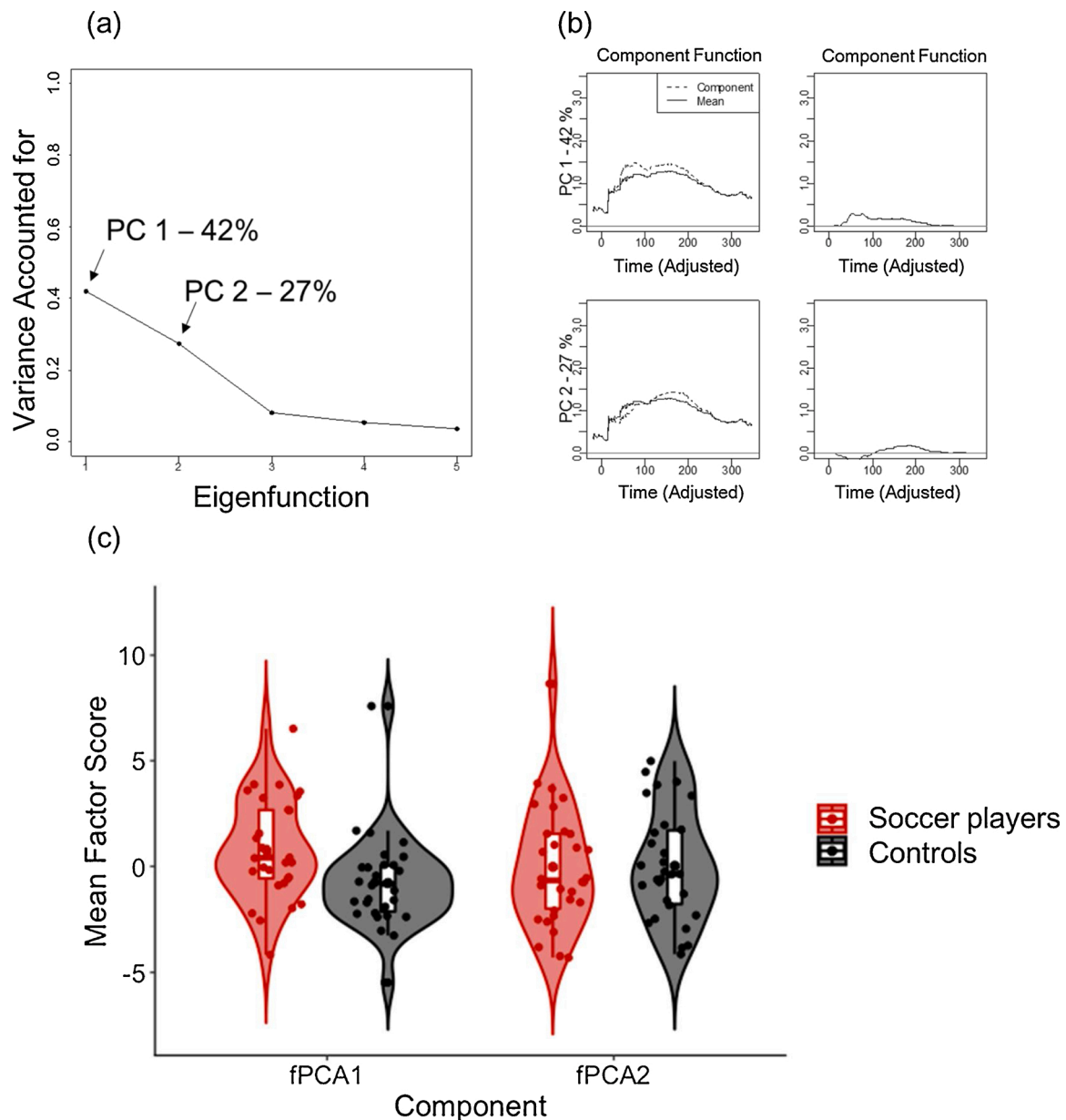


Fig. 4. (a) A screen plot showing the amount of variance accounted for by each Eigen function, ordered from highest to lowest. (b) The first two principal components of the capacity function. The left column shows the component functions, weighted by the average magnitude of the factor score, compared to the mean. The right column shows the component function weighed by the average magnitude of the factor score. (c) Violin plots for the distribution of fPCA components together with the mean (box central dot), median (box central line), first and third quartile (box edges), minimum and maximum (whiskers), and each participants (dots).

and $p < .001$), while no difference was observed between the P3 latency at Fz and at Cz ($BF_{10} = 0.21$; $p = .373$). We also found weak evidence for the *electrode* \times *group* interaction [$BF_{Inclusion} = 0.65$; $F(2, 116) = 3.58$, $p = 0.031$, $\eta_p^2 = .06$]. Decomposition of the interaction revealed that, for controls, P3 latency was shorter at Pz (415.75 ± 30.62 ms) than those at either Fz (436.58 ± 37.10 ms) or Cz (433.43 ± 37.91 ms) (all $BF_{10} > 3$ and $p < .001$). In contrast, P3 latency was shorter at Pz (428.22 ± 42.49 ms) than that at Fz (435.75 ± 42.65 ms) ($BF_{10} > 3$; $p < .001$) for soccer players, but only anecdotally shorter at Cz than at Fz (435.48 ± 43.36 ms) ($BF_{10} < 1$; $p = .054$). Further, we found support for the main effect of *condition* [$BF_{10} = 7.26e+10$; $F(1, 58) = 14.11$, $p < 0.001$, $\eta_p^2 = .20$], with the P3 latency significantly shorter in the redundant-target condition (420.77 ± 40.98 ms) than that in single-target condition (440.97 ± 45.33 ms). There was also strong evidence for the *condition* \times *group* interaction [$BF_{Inclusion} = 6991.73$; $F(1, 58) = 7.20$, $p = 0.010$, $\eta_p^2 = .11$]. Decomposition of the interaction revealed an effect of *condition* for the

soccer players (all $BF_{10} > 3$; $ps < .001$) but not for controls (all $BF_{10} < 1$; $p = .336$) (Fig. 5c). We also tested additional models, for which we found no meaningful support: one with *group* only [$BF_{10} = 6.73e-13$; $F(1, 58) = .22$, $p = 0.639$], as well as the *electrode* \times *condition* interaction [$BF_{Inclusion} = 0.65$; Greenhouse-Geisser corrected: $F(1.435, 83.21) = 1.41$, $p = 0.249$] and the *condition* \times *electrode* \times *group* interaction [$BF_{Inclusion} = 0.04$; $F(2, 116) = .72$, $p = 0.488$].

3.6. EEG time-frequency analysis

3.6.1. Alpha phase coherence over the midline fronto-parietal area

As shown in Fig. 6, we investigated inter-trial EEG phase coherence during a perceptual decision-making task and found that both redundant-target and single-target conditions exhibited clear increases in theta (4–7 Hz) and alpha (9–13 Hz) activities after stimulus onset. The upper panels of Fig. 6 showed that soccer players exhibited greater

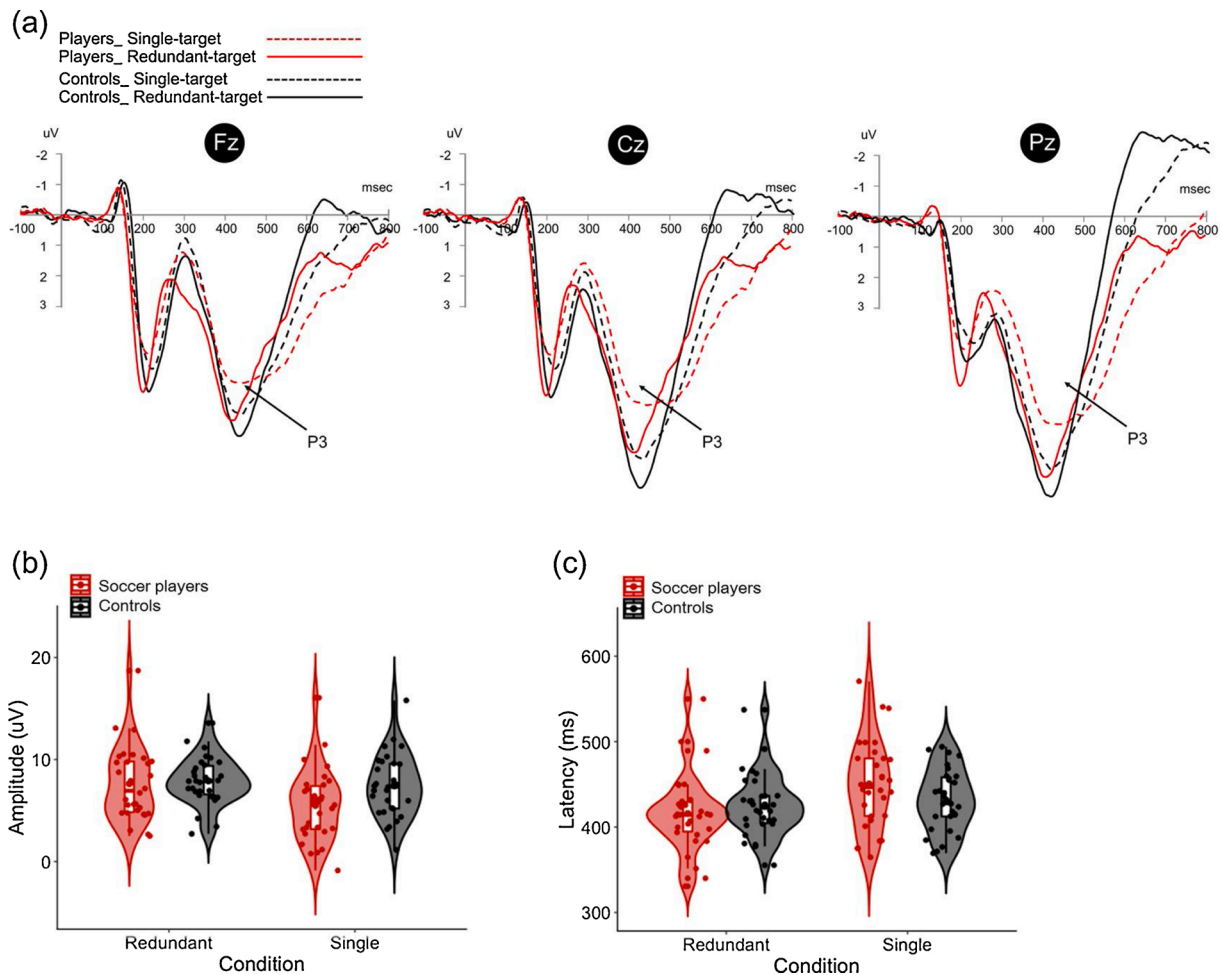


Fig. 5. (a) Grand averaged event-related potential waveforms across different conditions and electrodes for soccer players and controls. P3 amplitude (b) and P3 latency (c) across redundant-target and single-target conditions for each group, split by condition, illustrating the *group × condition* interaction. The plots show the distribution (violin) of amplitudes and latencies for the P3 component together with the mean (box central dot), median (box central line), first and third quartile (box edges), minimum and maximum (whiskers), and each participants (dots).

phase consistency within the alpha band for redundant-target condition compared to that seen for single-target condition after target onset (100–500 ms, 9–12 Hz) (all $q_s < 0.05$, FDR corrected). However, such an effect was not observed for the controls (all $q_s > 0.05$, FDR corrected) (lower panels of Fig. 6). No between group differences were observed when comparing soccer players with controls across conditions (all $q_s > 0.05$, FDR corrected).

3.7. Behavior-EEG correlations

3.7.1. RG of mean RT

The results showed weak evidence for the correlations between RG of mean RT and RG on P3 amplitude ($BF_{10} = 1.15$; $r = -0.23$, $p = .084$), P3 latency ($BF_{10} = 0.83$; $r = .20$, $p = .131$) and alpha ITPC (all $q_s > 0.05$, FDR corrected) (Fig. 7a).

3.7.2. The first principal function of fPCA

Results showed evidence for the correlation between the first principal function and RG on P3 amplitude ($BF_{10} = 2.27$; $r = -0.27$, $p = .035$), and P3 latency ($BF_{10} = 3.01$; $r = .29$, $p = .024$), while such an effect was weak for alpha ITPC (all $q_s > 0.05$, FDR corrected) (Fig. 7b).

3.7.3. The second principal function of fPCA

The correlation analysis revealed that the second principal function was not correlated with RG on P3 amplitude ($BF_{10} = 0.62$; $r = .17$, $p =$

$.199$), P3 latency ($BF_{10} = 0.35$; $r = .08$, $p = .529$), and alpha ITPC (all $q_s > 0.05$, FDR corrected) (Fig. 7c).

4. Discussion

Here, we report the first neurophysiological study combined with a novel and diagnostic mathematical tool (i.e., SFT) that investigated the cognitive and neural mechanisms underlying perceptual decision-making in team sports players. Our primary findings demonstrated that soccer players exhibited larger workload capacity than controls while making faster decisions despite no differences in mean measures (i.e., accuracy and mean RTs) being observed. Further, we observed clear RGs on ERP/EEG data selectively for the soccer players but not for the controls, together with RGs on P3 being positively related to workload capacity over faster responses. To this end, these findings suggest that soccer players and controls differed in the way how they processed multiple sources of information with the presence of a distractor.

The behavioral observation that soccer players' overall mean RTs were comparable to that of controls is consistent with numerous previous studies failing to observe superior processing speed in other team sports players (Alves et al., 2013; Pesce et al., 2007; Verburgh et al., 2014; Wylie et al., 2018). Although there is research claiming that superior processing speed may be a contributing factor to perceptual-cognitive expertise in sports (Chaddock, Neider, Voss, Gaspar, & Kramer, 2011), this idea might not generalize to all athletic

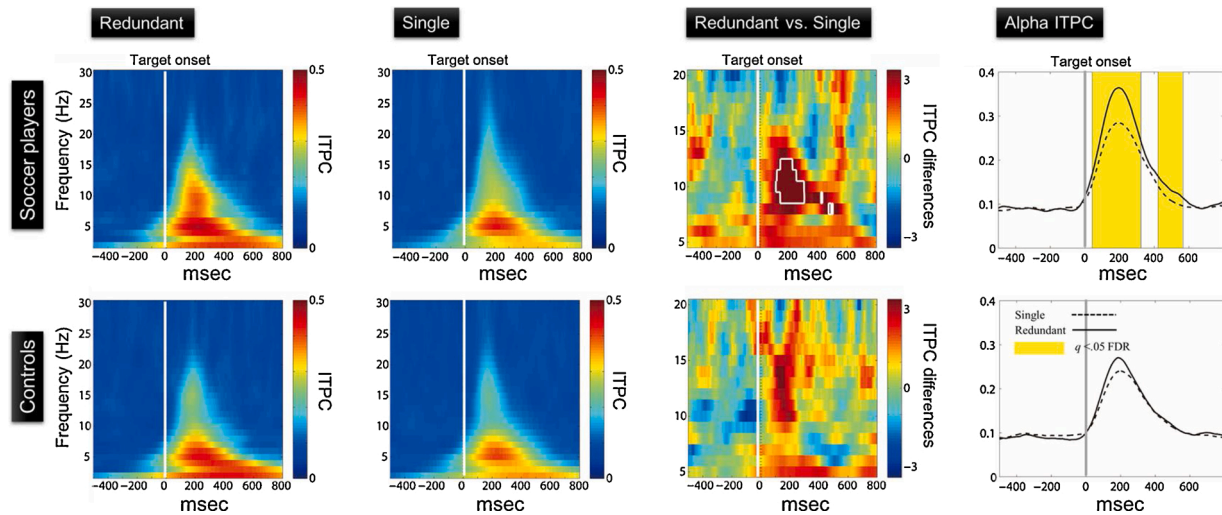


Fig. 6. Time-frequency decomposition with Morlet wavelets in the fronto-parietal regions (Fz, Cz, Pz). The upper and lower panels illustrate the target-locked ITPC (stimulus presented at $t = 0$) in soccer players and controls, separately. Redundant-target condition is shown in the first panels, single-target condition is shown in the second, and the average differences between the two (masked at $q < 0.05$ FDR correction) are shown in the third and fourth panels, with the white-line enclosed regions and yellow shadows representing temporal clusters that reach the significance level when comparing redundant-target and single-target conditions (at $q < 0.05$ FDR correction). Averaged ITPC over 9 – 13 Hz was significantly greater during redundant-target condition relative to single-target condition in the soccer players ($q < 0.05$ FDR correction), whereas such an effect did not reach the significance level in the controls. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

populations. For example, one meta-analysis study reported that athletes practicing team sports or static sports did not exhibit significant advantages over non-athletes on a variety of measures of attention and processing speed (Voss, Kramer, Basak, Prakash, & Roberts, 2010). One underlying reason might be that expertise is very narrow and does not translate to tasks beyond sport-specific contexts (i.e., near transfer) (Memmert et al., 2009). In addition, task difficulty might also account for the lack of mean performance differences, given that the accuracy rates for both groups were relatively high. Despite these limitations, there is increasing evidence that team sports players outperform non-athletes in tests of a subset of higher-order cognitive processes (e.g., executive functions) (Alves et al., 2013; Krenn et al., 2018; Vestberg, Gustafson, Maurex, Ingvar, & Petrovic, 2012; Wylie et al., 2018). Obviously, there is a lack of consistency in the literature on the relationship between team sports expertise and cognitive advantages.

Notably, most of the previous investigations have relied heavily on mean measures (e.g., mean RTs and accuracy) to make inferences regarding the cognitive advantages of athletes. However, some valuable information may be ignored in such measures. For example, although RG of mean RTs is typically considered a processing advantage because it suggests improved speed of responding, it lacks mechanistic explanation to interpret individual differences in processing capacity, such as the problem of model mimicry (Chang & Yang, 2014; Townsend & Wenger, 2004; Yang et al., 2019), and thus possibly leading to the fact that the cognitive advantages of athletes may have been underestimated. Here we considered that workload capacity is a more sensitive measure to infer the underlying mechanism of the information processing system.

The non-parametric capacity measure, $R(t)$, was calculated by comparing the distribution of the RTs taken to make correct responses to displays with two targets versus one target and one distractor. The results revealed marginal evidence showing more supercapacity individuals in soccer players compared to controls at the fast responses. This finding was further confirmed by an fPCA analysis (Burns et al., 2013), which identified important components characterizing capacity variation across time and participants. The first component, exhibiting an overall increase of the resilience function for the fast responses, separated soccer players and controls, providing support for the argument that the two groups processed multiple-signal information

differentially when making faster decisions. This effect, however, was not observed for the second component, suggesting that the later responses only weakly accounted for the group variation. Together, these findings suggest that soccer players may deal with multiple sources of information in a more efficient way than controls, especially when making faster decisions.

Although processing capacity is logically independent of other processing properties, we speculate that individual differences in processing architecture may help explain our SFT findings. This is because, empirically, certain architectures may possess a range of processing capacity (e.g., Townsend & Nozawa, 1995). For example, a coactive system is likely to be of supercapacity; a standard parallel system is of unlimited capacity; and a standard serial system is assumed to be of limited capacity. In the coactive system, activation from each channel is thought to be integrated into a single accumulator, resulting in a more efficient decision. As a result, the current findings may imply that soccer players tend to process multiple signals in a coactive fashion, whereas controls are more likely to process multiple signals via a parallel system with facilitatory interaction, or serially. That is, activation from the two channels may be processed simultaneously and compete for the decision independently; or, multiple signals are processed in sequence, one at a time, resulting in an inefficient decision.

It should be noted that the degree to which the processing of distracting information may affect the inferences about processing efficiency derived from the resilience capacity function (Little et al., 2015). That is, the assessment of the resilience capacity can be largely affected by the distractor processing because the resilience function is defined as the relative rates of processing of two targets to the processing of a target and a distractor. When the coactive model is applied, assuming that both target and distractor information are accumulated into a single accumulator (Little et al., 2015), the level of resilience capacity is dependent on whether the distractor can be processed efficiently or not. For example, if the distractor processing slows down the processing for the target, then the denominator in the Eq. (1) becomes smaller, which in turn results in a larger processing capacity. However, given similar performance of single-target processing across groups in the present case, the possibility that the soccer players were less efficient to process distracting information can be ruled out. Instead, our results suggest that they were more efficient at dealing with multiple signals and resolving

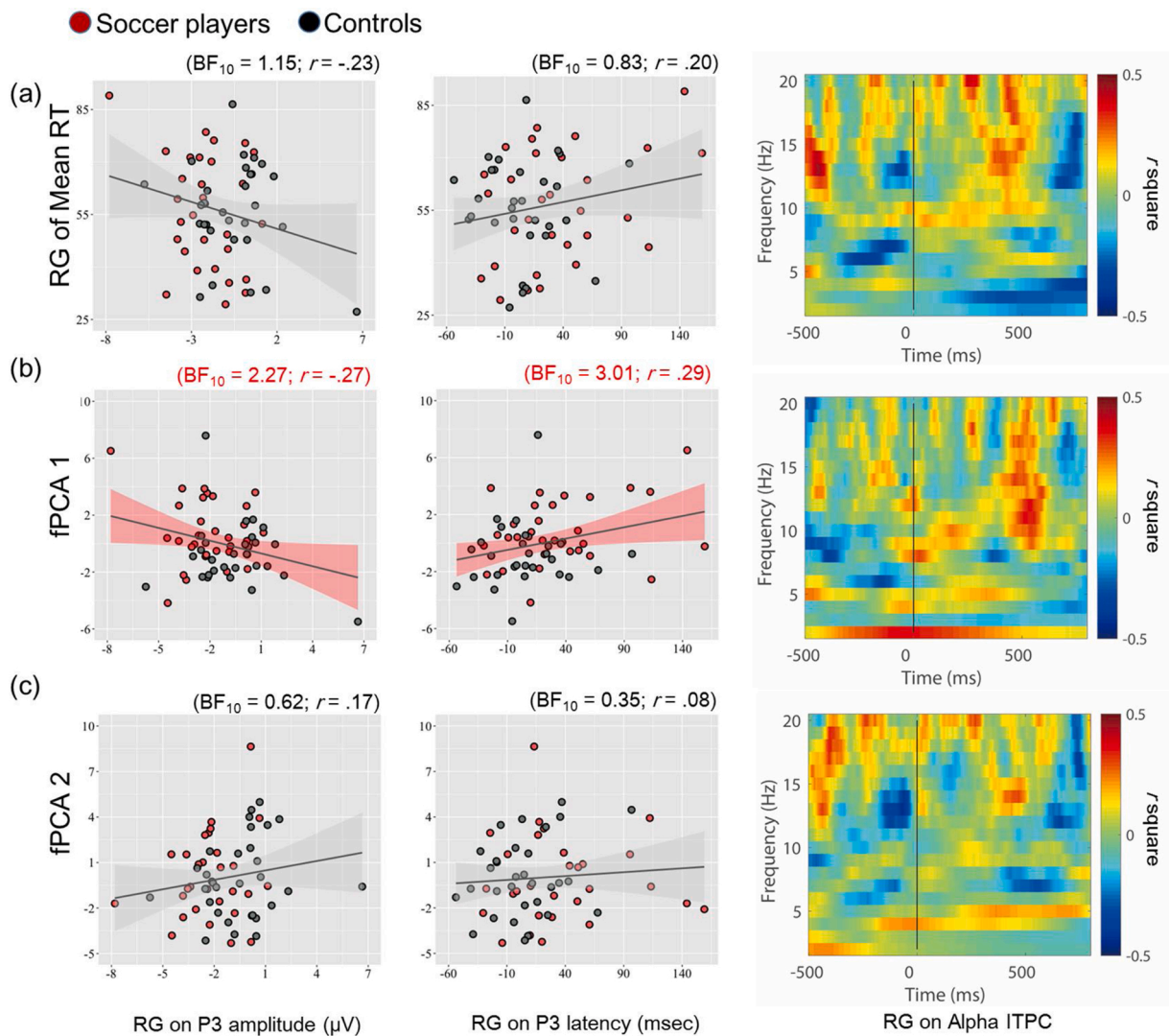


Fig. 7. The behavior-EEG correlations in terms of (a) RG of mean RT, (b) the first principal function of fPCA, and (c) the second principal function of fPCA. The results revealed that only the first principal function of fPCA significantly correlated with redundancy gain on P3 amplitude ($r = -.27, p = .035$) and P3 latency ($r = .29, p = .024$). Other redundancy gains on behavior-EEG correlation did not reach the significance level.

conflicting sources of information pointing to different decisions.

With regard to ERP findings, analyses of P3 component pointed out group differences in cognitively modulating neural activity. Here we observed that only the soccer players showed enhanced and earlier P3 during the processing of two targets relative to the processing of one target and one distractor. Specifically, such RGs of P3 were found to be correlated with workload capacity over faster responses. P3 has been known to play a pivotal role in exploring the mechanisms underlying the translation from perception into action during decision making (Kok, 2001; Nieuwenhuis et al., 2005; Twomey et al., 2015). Specifically, P3 amplitude is thought to reflect the amount of attention paid to a given stimuli (Johnson, 1993; Kao et al., 2019; Wang, Shih, & Tsai, 2016), while its latency has been associated with the speed of stimulus-evaluation processes (Duncan-Johnson, 1981; Kutas, McCarthy, & Donchin, 1977). Prior research has reported greater modulation of P3 along with more efficient responses when simultaneously presenting two targets relative to a single target during a visual discrimination task (Akyürek & Schubö, 2013), which the authors interpreted as being related to the ease of consolidation of target signals in working memory, an argument in line with the context-updating hypothesis of P3 (Donchin & Coles, 1988; Polich, 2007). Thus, the P3 modulations seen in soccer players may reflect a greater level of attentional resources

engaged and accelerated neural responses when simultaneously processing two target signals, resulting in greater processing capacity.

Information-processing models may help explain our findings. First, when applying the coactive model (Miller, 1982), the two targets in the redundant-target condition of our experiment may concurrently contribute to activation of the joint representation, which may result in the RG of P3 and greater workload capacity seen in the soccer players. In contrast, the weakness of RG on P3 in controls may suggest that the redundant information was not processed coactively, which could presumably be explained by the race model (Mishler & Neider, 2017), in which target features race against each other for a decision.

Our findings are also interesting in the context of dimensional-action model (Cohen & Feintuch, 2002). According to this model, when attention is focused on two target signals, the response decision from both signals are co-activated. Alternatively, when attention is focused on one of the target signals, only the response decision associated with the attended target is transferred to centers responsible for response execution. Thus, our findings possibly reflect differences processing strategy between soccer players and controls. To elaborate, soccer players were more likely to simultaneously attend to the two target signals, thus resulting in more information being processed. In contrast, controls might tend to focus on one of the target signals, and thus other

signals do not contribute to further processing.

Despite the absence of correlations between alpha ITPC and behavioral observations, the EEG finding provides supportive evidence for the ERP results due to the similarity of functional role of alpha phase and P3 in task processing (Yordanova & Kolev, 1998). Results revealed that soccer players, but not controls, exhibited greater alpha ITPC on redundant-target trials relative to single-target trials. Alpha activity has been observed in a variety of attention tasks (Haegens, Händel, & Jensen, 2011; Klimesch, 2012), and its phase activity is thought to be a manifestation of controlled enhancement in target detection process (Busch et al., 2009). Yordanova and Kolev (1998) reported enhanced alpha phase synchronization when detecting targets relative to non-targets in an oddball paradigm, presumably reflecting a mechanism that stabilizes alpha brain states in response to task-relevant information processing. Further, Hanslmayr et al. (2005), using a visual discrimination task, found that alpha phase synchronization was stronger for good performers, possibly reflecting better coordination in cortical activation processes. It seems conceivable that the higher alpha ITPC on redundant-target trials may be related to coactive processing of the target signals, and the differential modulation of alpha phase between soccer players and controls may suggest that they process redundant information in a different manner. If this is the case, we postulate that the additional processing of the redundant target may elicit more stable cortical responses in soccer players. In contrast, controls may be limited in processing multiple signals such that the summed-up processes may not induce noticeable changes in alpha activity.

Finally, it is also worth mentioning that the absence of redundancy gain on neural processes in controls might be linked to baseline performance in the general population. Healthy adults typically display unlimited-capacity processing for color and shape features (Mordkoff & Yantis, 1991; Yu et al., 2014), and our data collected here suggest that team sports expertise may be related to cognitive advantage in processing multiple sources of information, possibly indicative of a tendency to adopt a global and flexible processing strategy to deal with real-world sporting environments.

We should also point out a number of potential limitations to the present study. First, this study only investigated the processing capacity in a redundant-task detection task involving single modularity (i.e., two different visual features) within one location. However, research has demonstrated that processing capacity differ depending on task designs, with evidence showing that most individuals with superior capacity in processing information with different modalities (visual and auditory modality) and most individuals with limited-capacity in processing information presented in different visual fields (Yu et al., 2014). Thus, future studies could also address this issue by using different types of redundant-target designs. Second, although we observed the mechanism of co-activation at a central, decisional level as evidenced by the modulations of P3 and alpha ITPC, other loci of co-activation such as perceptual processes (Mordkoff & Yantis, 1991) or motor components (Giray & Ulrich, 1993) may also possibly contribute to greater processing capacity seen for team sports expertise—it would thus be interesting to explore whether the locus of enhanced processing capacity in team sports players differs depending on task characteristics. Third, this study did not control for some pre-existing differences that may potentially influence the variability in cognitive abilities, such as intelligence quotient (Fry & Hale, 2000), socioeconomic status (Hackman & Farah, 2009), personality (Hsieh, Yu, Chen, Yang, & Wang, 2020), or actual stress level (Hynynen, Uusitalo, Konttinen, & Rusko, 2008). Further investigations should aim to incorporate these factors to understand their confounding associations with athletes' information processing capacity. In addition, given that physical fitness has been associated with cognitive individual differences (Ludyga, Mücke, Colledge, Pühse, & Gerber, 2019; Wang, Moreau, Yang, Lin et al., 2019), our findings may possibly reflect this association. However, it is worth noting that recent research using meta-regression analysis has revealed that exercise dose parameters (e.g., frequency, session duration and

intervention length) did not individually contribute to exercise-induced cognitive benefits (Ludyga, Gerber, Pühse, Looser, & Kamijo, 2020; Moreau & Chou, 2019), suggesting that long-term exercise training may improve cognitive performance even without noticeable changes in physical fitness (Wang, 2020). One may also argue that general physical activity might have impacted the results of interest (Kamijo & Takeda, 2013; Kao et al., 2019). In order to alleviate this concern, we recruited physically active non-players as the control group. Unfortunately, we still could not deny the possibility that physical activity may account for some proportions of variance in the outcomes seen here. This is because this study did not precisely quantify the amount of physical activity level for each participant. However, one should be aware that it is difficult to objectively measure the physical activity level for some soccer-specific practices (e.g., motor, skill, tactical trainings, and small-side games), and, notably, the qualitative characteristics of sport training (e.g., cognitive skill and motor complexity) may also contribute to the observed cognitive enhancements (Ludyga, Gerber, Pühse, Looser, & Kamijo, 2020). Nevertheless, future research is needed to determine whether the perceptual decisions underlying team sports expertise might be mediated by the level of physical fitness or physical activity.

Despite these limitations, taken together, this study provides some preliminary evidence for the utility of SFT combined with EEG in understanding the cognitive and neural mechanisms underlying expert behavior in sports. In particular, the current findings suggest that the greater processing capacity seen in elite soccer players cannot be explained by mean performances, implying that the choice of measure could strongly influence the conclusions that are drawn. If this is the case, SFT may provide complementary evidence to solve some of the discrepancies in the literature. For example, although a recent meta-analysis study has demonstrated superior executive function in elite soccer players compared to their sub-elite and non-athletic peers (Scharfen & Memmert, 2019), such cognitive advantages did not emerge from those practicing other team sports (e.g., ice hockey, basketball) (Lundgren, Högman, Näslund, & Parling, 2016; Nakamoto & Mori, 2008). Given that the conflicting evidence could be in part attributable to the inherent differences in the cognitive demand or processing strategy across different team sports, SFT may offer an alternative explanation regarding the specific cognitive profile of team sports. Moreover, with regard to the need for further development and validation of cognitive measures that can be used to distinguish different levels of expertise and thus sports successes, future research is recommended to extend our findings by comparing soccer players with different levels of expertise. Finally, it is of interest to examine whether greater workload capacity in team sports players may be associated with higher level of attentional reserve under high cognitive workload. For example, despite the evidence that cognitive workload is negatively associated with attentional reserve (Jaquess et al., 2017), it remains to be determined whether individual difference in workload capacity may mediate such relationship.

5. Conclusion

This study provides an alternative mechanism of perceptual decision making in elite soccer players. While previous research has primarily explored processing speed advantage, in the current study we made use of the entire RT distribution and demonstrated greater processing capacity in soccer players when making faster decisions. This was observed in conjunction with more flexible neural modulations in response to variations in the number of information sources, possibly reflecting the information-processing characteristics of team sports players during perceptual decisions. Despite the inherent limitations of our cross-sectional design, the present findings may provide the basis for understanding experience-dependent changes in perceptual decisions, possibly an essential pre-requisite for the development of team sports expertise.

Declaration of Competing Interest

We declare no competing financial interests.

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