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Psychology of Sport & Exercise 78 (2025) 102808

Contents lists available at ScienceDirect

Psychology of Sport & Exercise

journal homepage: www.elsevier.com/locate/psychsport

The structure of executive functions in athletes: A latent variable approach☆

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ARTICLE INFO

Keywords:
Cognitive ability
Athletes
Factor analysis
Executive function

ABSTRACT

The role of executive function (EF) in expert sport performance has become a popular topic in sport and exercise psychology research. Research in this area often adopts the unity/diversity framework of EF (i.e., inhibition, shifting, and updating). However, recent investigations into the suitability of this unity/diversity model, and other competing models (e.g., the nested model of EF), has questioned whether this model is suitable for across all populations (e.g., athletes). The aim of the present study was to use confirmatory factor analysis to outline the most suitable EF model in a sample of athletes. In total, 131 participants with varying levels of athletic expertise completed two inhibition, shifting, and updating tasks. All analyses were performed in RStudio. The results revealed the nested model of EF provided the best fit to the data indicating its suitability for athletes. Acceptable fit was also found for the unity/diversity mode of EF. Overall, the results suggest that, despite recent criticism of the nested model and unity/diversity framework of EF, such structures appear to be suitable for use with athletic populations.

1. Introduction

Miyake and colleagues (2000) examined the distinctiveness of three widely accepted executive functions (EFs): inhibition, shifting, and updating. Miyake et al.'s (2000) seminal work demonstrated that these functions were related, but also distinct. While substantial correlations existed between the EFs, each also played a unique and individual role. As a result, inhibition, shifting and updating can collectively be referred to as the unity/diversity lower-order model of EF. This model has been used to better understand EF in a variety of populations, including athletes (e.g., Brimmell et al., 2021). However, recent work has questioned the accuracy of this lower-order model. Specifically, Sambol et al. (2023)outlined that a united, yet diverse, model structure for EF was not appropriate in their sample as factor analysis results suggested poor model fit (i.e., the unity/diversity structure did not replicate). The work of Sambol and colleagues (2023) raises questions about the EF model's suitability and suggests further work is needed to understand whether such EF models are appropriate in the sport context.

1.1. Executive function and athletes

The three most popular lower-order EF comprise inhibition (i.e., withholding task-inappropriate responses), shifting (i.e., attentional switching between tasks or information), and updating (i.e., manipulating content within working memory; Miyake et al., 2000). These EFs, among others, may be particularly pertinent for athletes. For example, sports that are open or externally paced (e.g., basketball and football) require athletes to respond to dynamic, rapidly changing environments, relying significantly on EF (Koch & Krenn, 2021). Take a basketball player in possession of the ball; they must coordinate their body and the ball, update positional information of teammates and opposition, and simultaneously make optimal situational decisions (e.g., pass, shoot, or dribble the ball). In such situations, athletes need to be both effective and efficient at inhibiting, shifting, and updating. Given the unique demands of sport and exercise it is possible that the dependence on EFs may differ between athletes and non-athletes (e.g., university student samples; Miyake et al., 2000) with several potentially differentiating factors previously outlined (e.g., sport type; Krenn et al., 2018,

☆ Author note: Data files and code are open access via the Open Science Framework - https://osf.io/xtyr4/.

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https://doi.org/10.1016/j.psychsport.2025.102808
Received 9 September 2024; Received in revised form 17 January 2025; Accepted 20 January 2025
Available online 22 January 2025

expertise; Hagyard et al., 2021).

The EFs of inhibition, shifting, and updating are believed to be key attentional components of goal-directed behaviour (Eysenck et al., 2007). The brain region that appears to be the most active during goal-directed behaviour is the prefrontal cortex (i.e., when performing tasks that require these EFs, electroencephalography research shows activation in this region; Collette & Van der Linden, 2002). The prefrontal cortex, like most brain regions, is a highly plastic structure capable of adaptation based on usage (a 'use it or lose it' approach; Shors et al., 2012). Specifically, adaptations can come in the form of structural or functional changes that can occur via increased oxygenated blood flow to a region or through repeated synaptic activation (Giles et al., 2014). Athletes are individuals who, more regularly than non-athletes, experience increased oxygenated blood flow to the prefrontal cortex due to increased time spent exercising (Kimura et al., 2022) and are often involved in goal-directed sport which produces synaptic activity within the prefrontal cortex. Therefore, it is not farfetched, due to increased exercise levels and engagement with goal-directed behaviours, to believe that the structural or functional configuration of the prefrontal cortex is different in athletes compared to non-athletes. Therefore, it should not be a given that theoretical frameworks of EF that work for non-athletic samples will simply work in athletic samples.

In a recent review of 142 studies that examined cognitive ability and sport performance in competitive athletes, Kalen and colleagues (2021) reported a medium effect size for the overall difference in EF scores, with higher skilled athletes performing better on tests of EF compared to lower skilled athletes. The apparent link between EF and highly skilled athletic performance corresponds to the relatively recent surge in commercial products designed to target and train EFs in athletes (Harris et al., 2018). However, the EF and athlete relationship isn't straight forward (for a review, see Furley et al., 2023). Furley et al. (2023) outlined that EFs typically targeted in domain-general tasks are void of sporting context and cannot facilitate far-transfer, only near-transfer (i.e., repeated performance of such EF tasks leads only to improvement in that task, or closely related ones, and not on field performance). This research casts some doubt on the ability of EF to predict athletic performance. Furley et al. (2023) also note that it's perhaps more likely that the impact of EF on athletic performance is not direct and instead, there are confounding variables in place where EFs interact with other key perceptual-cognitive processes (e.g., visual attention [VA]; Brimmell et al., 2021).

Numerous examples demonstrate a positive relationship between EF and athletic performance. Simonet et al. (2023) performed a scoping review on the relationship between inhibition and sports practice and suggested that overall, athletes show greater inhibition compared to non-athletes. Greater shifting ability has also been reported in 1st Swedish division soccer players compared to 2nd and 3rd division players (Vestberg et al., 2012). Similarly, the ability to update information in working memory has been shown to be greater in expert athletes (Vaughan et al., 2021). These examples all utilise domain-general measures of EF (i.e., tasks typically developed by cognitive psychologists that use every day stimuli void of any specific context) and thus could be susceptible to transfer. Recently, Knobel and Lautenbach (2023) tried to bridge the gap between domain-general and sport-specific EF tasks when they had participants complete a standard *n*-back task (a measure of updating; Jaeggi et al., 2003) and a football-specific *n*-back in a SoccerBot (Heilmann et al., 2021). Results suggested that the football-specific *n*-back showed good convergent validity compared to the standard *n*-back task for both response accuracy and response time.

Response accuracy and response time are very important outcome variables to consider when examining EF in athletes, though research often omits one of these. Indeed, Brimmell et al. (2021) outlined the important distinction between performance effectiveness (i.e., accuracy) and efficiency (i.e., accuracy by response time) often not considered in EF research. The distinction was first referred to in Attentional Control Theory (ACT: Eysenck et al., 2007) where it was outlined that during moments of anxiety or stress an individual could maintain, or increase, performance effectiveness on tasks measuring the EFs of inhibition, shifting, and updating (i.e., continue to be accurate on trials that place significant demands on the individual or include 'distractor' stimuli). The cost of such maintenance or improvement is that the individual must utilise more resources (e.g., time or effort; Eysenck et al., 2007) thus making them less 'efficient' (i.e., responses can be correct but at a higher cost). Research with athletes is a prime opportunity to include both effectiveness and efficiency scores given they are often, even in relatively closed sports (e.g., golf), in situations that demand they be accurate (e.g., keep the ball on the fairway) while under time constraints (e.g., shot penalties in golf if individuals take too long).

1.2. *Models of executive function*

Miyake et al. (2000) were the first to examine the structural relations between EFs. To analyse the degree of association (i.e., unity and/or diversity) between inhibition, shifting, and updating, Miyake and colleagues (2000) utilised confirmatory factor analysis (CFA). Miyake et al. (2000) included multiple measures of each EF to build latent variables, arguing that this approach provides a purer measure of the target EF. Miyake and colleagues (2000) showed that the three EFs were, to some degree, both united and diverse. The CFA showed that three unique factors emerged (inhibition, shifting, and updating) but were also moderately correlated supporting the unity/diversity framework of EF. Notably, this unity/diversity framework of EF showed greater model fit compared to an independent-factor model of EF (i.e., three unique factors) and a single-factor models of EF (i.e., a single composite factor). Miyake et al. (2000) employed structural equational modelling to confirm their proposition that inhibition, shifting, and updating are indeed fundamental components of cognition that influence higher-order EFs.

While the unity/diversity framework of EF is extensively cited, research questioned its validity (e.g., Friedman et al., 2008). In the initial framework, unity/diversity between latent EFs was assessed through factor correlation coefficients (Friedman & Miyake, 2017). Friedman et al. (2008) examined the unity/diversity component through the latent variables leading to the conception of the nested model of EF. The nested model introduced a "common EF" factor which is believed to facilitate goal maintenance and attentional bias (i.e., a bias toward goal-related stimuli; Friedman & Miyake, 2017). In this model, "common EF", accounts for any shared variance across inhibition, shifting, and updating tasks (i.e., model unity). The diversity component, and nested element, is accounted for by updating-specific and shifting-specific factors which account for any remaining variance not accounted for by the "common EF" factor (Friedman & Miyake, 2017). Despite ongoing debate regarding the most suitable EF structure, research on EFs in athletes have largely adopted the unity/diversity framework of EF without assessing its efficacy. This may partially explain some of the mixed results within the literature (e.g., Furley et al., 2023; Kalen et al., 2021).

The existence of various frameworks/models indicates a lack of clarity in the structure of EF. A notion highlighted and investigated by Sambol et al. (2023) who outlined that previous studies may use tasks that are too similar (thus inflating correlations/factor loadings). Consequently, studies like Miyake et al. (2000) and Friedman et al. (2008) may report high correlations and acceptable model fit due to procedural similarities between tasks rather than common underlying EF processes. To address this, Sambol and colleagues (2023) selected tasks that were procedurally diverse yet required the same EFs. The CFA results of Sambol et al. (2023) did not support the unity/diversity framework or the nested model of EF. Instead, their exploratory factor analysis (EFA) suggested a new model comprising working memory, cognitive flexibility, and a sole Stroop task factor. These results raise doubts around the structural configurations of EF, the EF conclusions adopting this framework, and the suitability of such models in general and specific populations (e.g., athletes). However, several potential shortcomings can be outlined in Sambol et al. (2023). The most pertinent being the fact that EFA (i.e., data reduction) and CFA (i.e., data specification) are different statistical techniques and outcomes are not directly comparable.

In the current work, CFA is believed to the most appropriate statistical approach. In terms of differences EFA and CFA are fundamentally different in their approach to how they look to place relatively high numbers of observed components (in this case, responses on EF tasks) on to fewer latent, or unobserved, variables (i.e., broader underlying constructs; Yong & Pearce, 2013). Specifically, EFA is normally the first step in factor analysis and is appropriate when there is no reason to believe the observed components will conform to a particular structure. However, CFA attempts to confirm a particular hypothesis and in doing so, restricts the structural variance to that which falls within the predicted model (Yong & Pearce, 2013). Here, CFA is far more appropriate than EFA given that we have four very specific hypothesised models that have been obtained from previous research (i.e., the unity/diversity framework of EF, the independent-factor model, the single-factor model, and the nested model of EF).

1.3. The present study

To date, little research has examined the factor structure of EFs in athletes with the only known example forming a small part of a wider examination in to the role of EF, attention, and emotion in predictive athletic performance (Bisagno et al., 2022). Moreover, no work has been conducted into which specific EF model (i.e., the unity/diversity framework of EF, the independent-factor model, the single-factor model, or the nested model of EF) is the most appropriate for athletic populations. Athletes are special as they regularly engage in exercise causing increased oxygenated blood flow within the prefrontal cortex and engage in goal-directed behaviour frequently within their sport. As a result, it is likely that the structure and functionality of the prefrontal cortex, and thus the key EFs of inhibition, shifting, and updating may differ. Therefore, an examination of whether models created based on the performance on EF tasks of non-athlete samples is relevant for athletes is warranted. The absence of such studies with athletes, coupled with recent concerns about previous EF models, highlights the need to empirically test the structure of EFs in athletes.

This is particularly crucial given the variety of previously proposed models, many of which lack of support (Sambol et al., 2023). Although Sambol and colleagues (2023) suggested the unity/diversity framework and nested model of EF may not be suitable for all populations they did not test the independent-factor and single-factor models. Therefore, such options should not be ruled out when working with new populations (e.g., athletes). To date, despite the widespread adoption of lower-order models of EF in the literature (e.g., Brimmell et al., 2022; Vaughan & Edwards, 2020), there is no existing evidence to ascertain whether these EF models are appropriate for use with athletes. The absence of an accepted framework to test EF in athletes may reduce precision and, consequently, confidence in findings. The aim of the present work was to use CFA to determine which of the proposed EF structures is most suitable in a sample of athletes for both EF effectiveness (i.e., accuracy) and efficiency (i.e., accuracy by time; Brimmell et al., 2021). It was hypothesised that, despite the work of Sambol and colleagues (2023), the most popular model of EF (i.e., the unity/diversity framework of EF) would be the most suitable model in our athletic sample.

2. Methods

2.1. Design and ethics

The present study was conducted via the cloud-based platform Gorilla (Anwyl-Irvine et al., 2020). Online platforms allow for remote testing and have been shown to bring equivocal findings to laboratory-based studies (e.g., Brimmell & Vaughan, 2022; Ziv & Lidor, 2021) and have been previously applied in sport and exercise research (Erdogdu et al., 2023). Moreover, outcome variables derived from reaction time and response accuracy, which are key within the present study, have been noted as comparable across laboratory and online settings (Brimmell & Vaughan, 2022; Hilbig, 2016). The current study received institutional ethical approval from the lead authors institutional ethics committee.

2.2. Participants

Initially, 135 participants completed the present study. However, the data of four volunteers who did not provide sport participation information was removed ($N = 131$; $M_{\text{age}} = 27.15 \pm 10.32$ years; 54% were male). The total sample size followed Kline's (2023) recommendation of 5–10 participants per parameter for sufficient power for CFA, and is consistent with previous research (e.g., Miyake et al., 2000; Sambol et al., 2023). Participants responded to questions regarding athletic expertise to ascertain a continuous score of athletic engagement (as in Brimmell et al., 2021; Hagyard et al., 2021; see also Swann et al., 2015). Specifically, expertise was calculated using Swann et al.'s (2015) recommendations where a composite score is created based on individual highest performance level, sporting success, sporting experience in years, competitiveness of the sport in the individual's residing country, and global competitiveness of the sport (see Brimmell et al., 2021, for more detail). As all expertise scores were above zero (mean athletic expertise = 4.44, $SD = 2.34$, range = .67–12.00), we can confirm that all participants could be considered athletic to some degree.

2.3. Measures

Each EF measure was selected based on regular application within research examining EFs in athletes, acceptable validity scores reported in previous research, and acceptable reliability scores reported in previous research. Validity and reliability values were not obtained in sport-specific studies but in studies aiming to assess the psychometric properties (i.e., validity and reliability) of the EF tasks themselves. All psychometric data, including reliability scores for the EF tasks in the present sample, is presented in Table 1.

2.3.1. Inhibition

Stop Signal Task (SST). The SST (Logan & Cowan, 1984; Verbruggen et al., 2019) required participants to respond to the direction of a central facing arrow (i.e., go trials). The target arrow was either facing left (requiring a "F" key press) or right (requiring a "J" key press). The stop signal was the emergence of a red ring around the target arrow which indicated participants should withhold their response and await the next trial. The stop signal was presented on 25% of the trials (i.e., stop trials). The task adopted a staircase design which adapted to participant performance and aimed for a 50% success rate (Hagyard et al., 2021; Verbruggen et al., 2019). Specifically, the stop signal delay, which is first presented after 250ms, increased by 50ms when successful and decreased by 50ms when unsuccessful on a stop trial. Participants completed 10 practice trials and two blocks of 100 trials. The outcome measure of effectiveness was the number of correct responses on stop trials minus incorrect responses on stop trials. Efficiency was Stop Signal Reaction Time which was calculated following Verbruggen et al.'s (2019) recommendations (i.e., multiplying the number of successful go responses by the probability of responding on a stop trial, then subtracting the average Stop Signal Delay from this new variable).

Go/No-Go Task (GNGT). The GNGT (Gordon & Caramazza, 1982) involved the presentation of a continuous stream of alphabetic letters that require either a go or no-go response. The stimuli in the present task were the letter "K" (the go response letter) and the letter "L" (the no-go

Table 1
Psychometric properties of EF measures used in the present study.

EF Measure	Validity	Reliability	Reliability in Current Sample
Stop Signal Task	Factor loading = .50 with other measures of inhibition (Gunten et al., 2020)	Sound split-half reliability (r = .97; Gunten et al., 2020)	α = .88[b]
Go/Go-No Task	Small-moderate correlation with other inhibition measures (r = .20; Gunten et al., 2020)	Sound internal consistency (α = .89; Gunten et al., 2020)	α = .96[b]
Colour-Shape Task	Factor loadings >.50 with other measures of shifting (Friedman et al., 2016)	Sound split-half reliability (r = .85; Friedman et al., 2016)	α = .93[b]
Modified Flanker Task	Moderate correlation with other measures of shifting (r = .52 [a]; Zelazo et al., 2014)	Strong test-retest reliability (r = .85[a]; Zelazo et al., 2014)	α = .94[b]
2-Back Task	Moderate correlation with other updating measures (r = .40; Frost et al., 2021)	Strong test-retest reliability (r = .79; Soveri et al., 2018)	α = .89[b]
Backward Digit Span Task	Moderate correlation with other updating measures (r = .41; Geurten et al., 2016)	Strong test-retest reliability (r = .64-.84; Woods et al., 2011)	α = .86[b]

Notes.
[a] Validity and Reliability values taken for the Flanker Task, not specifically the Modified Flanker Task used here as no such assessment of this recent iteration yet exists.
[b] Reliability was calculated using Kuder-Richardson Formula 20 due to binary data.

response letter). When “K” was presented on-screen, participants were to press the spacebar key and when “L” was presented on-screen, participants were to withhold any response. To build a prepotent response and ensure inhibition was being examined, go trials made up 75% of the task trials, while no-go trials made up 25% of the trials. Participants completed eight practice trials and two blocks of 100 trials. Effectiveness was measured by subtracting incorrect responses (i.e., false alarms) from correct responses (i.e., successful inhibitions). Efficiency was calculated by dividing effectiveness scores by mean reaction time (RT) on correct go trials.

2.3.2. Shifting

Colour-Shape Task. The colour-shape task (adapted from Friedman et al., 2008) presented participants with one of four visual stimuli (i.e., blue square, blue rectangle, green square, or green rectangle). Participants were asked to categorise the presented stimuli based on a cue word (i.e., colour or shape). When categorising the stimuli for colour, participants pressed “J” for green and “F” for blue and when assessing for shape, participants were required to press “J” for square and “F” for rectangle. For example, the presentation of a green rectangle with the cue shape, would require an “F” response. Participants completed four practice trials and two blocks of 48 trials. Cue words and stimuli were presented randomly, but an equal number of times. That is, each stimuli appeared 12 times and each cue word 24 times, per block. Outcome measures were calculated based on trials that involved a switch, that is, when the cue word switched from colour to shape, or vice versa. Effectiveness was calculated by subtracting incorrect responses from correct responses on switch trials. Efficiency was calculated by dividing effectiveness scores by mean RT on correct switch trials.

Modified Flanker Task. The modified flanker task (based on Krenn et al., 2018) involved identifying the direction of a black-coloured central target arrow flanked by congruent (i.e., facing the same direction as the target) or incongruent (i.e., facing the opposing direction to the target) distractor arrows. Participants pressed the “Z” key for left facing target arrows and “M” key for right facing target arrows. On certain trials, the target arrow was red which meant participants were to respond with the opposite key (e.g., “Z” for a right facing target arrow). Additionally, the target arrow could be green (which required the same responses as when black) or up-facing instead of the sideways (which required no response at all). Participants completed three blocks of 8 practice trials (one for black target arrows, one for red target arrows, and one with all target arrows) and two blocks of 126 trials. Outcome measures were calculated based on trials that involved a switch (e.g., target arrow switched from red to black). Effectiveness was indexed by subtracting incorrect responses from correct responses on switch trials. Efficiency was calculated by dividing effectiveness scores by mean RT on correct switch trials.

2.3.3. Updating

2-Back Task. In the 2-Back task (Jaeggi et al., 2003) a continuous stream of alphabetical letters was presented to which the participant must recall if the currently displayed letter matches the one displayed two trials before or not. When the current letter matched the one two trials prior, the participant was to press the “F” key and press the “J” key if the current letter was not a match. Participants completed six practice trials and three blocks of 20 trials. The outcome measure of effectiveness was calculated by subtracting the number of incorrect responses from the number of correct responses. The efficiency measure was calculated by dividing effectiveness scores by the mean RT of correct responses.

Backward Digit Span Task. The backward digit span task (Reynolds, 1997) presented participants with a string of numerical stimuli (string length ranged from 3 to 9) and at the end of each presentation, they had to recall the digits in reverse order. Backward digit span was used over the forward digit span as it is believed to require updating and working memory abilities and the forward span is not (Reynolds, 1997). Participants completed two practice trials and three blocks of seven trials. Effectiveness was measured by the number of correctly recalled spans minus the number of incorrectly recalled spans. Efficiency was calculated by dividing effectiveness scores by mean RT on correct trials.

2.4. Procedure

After opening the online Gorilla link, participants created a pseudonym to protect anonymity before reading an information sheet and providing informed consent to partake. Next, participants provided demographic information including: any visual impairment, age, gender, ethnicity, and sport expertise (to ascertain whether the participant could be classed as an athlete to some degree). The participants then completed the six tasks including: the SST, the GNGT, the Colour-Shape Task, the Modified Flanker Task, the 2-Back Task, and the Backward Digit Span Task. Tasks were completed in a counter-balanced order using the Latin Square feature in Gorilla. The study lasted approximately 70 min and ended with a brief thank you message, a debrief, and the opportunity for the participant to enter a voluntary prize draw (Amazon voucher ranging £10–50). The prize draw was voluntary as it required entering a personal email address to receive the prize therefore, those wishing to remain anonymous could do so.

2.5. Data analytic plan

Data analysis was conducted in RStudio (version 4.2.3; R Core Team, 2023). The associated datafiles and RStudio script are available via the Open Science Framework [https://osf.io/xtyr4/?view_only=25d7d5bab6924ddcb171851d75fe4a08]. Missing data was first screened within the datafile. Missing data comprised 3.91% of the entire dataset. As missing data was <5%, missing values were replaced with the item mean (Tabachnick & Fidell, 2007). Univariate normality was assessed by examining whether skewness values fell between −3 and +3 (Field, 2018) and whether kurtosis values fell between −10 and + 10 (Brown, 2015). This process revealed a single outlier for SST efficiency. This outlier was replaced with values three standard deviations from the mean (Friedman et al., 2008; Sambol et al., 2023), then univariate analyses were re-checked and no further deviances from normality were revealed (see Table 2). Multivariate normality was assumed, as a combination of univariate normality usually leads to a multivariate normal distribution (Brereton, 2015).

Descriptive statistics and correlations between all the outcome variables are shown in Tables 2 and 3, respectively. Correlations included between-task (e.g., SST & GNGT) and within-task (i.e., effectiveness & efficiency) relationships. Also, given the previously outlined role of expertise upon EF, our continuous expertise variable was included in correlational analyses. The Lavaan package (latent variable analysis; Rosseel, 2012) was used to perform the effectiveness and efficiency CFA models, respectively. A series of CFAs were selected over other latent modelling options (e.g., EFA) because the proposed structure of EF has been commonly reported (e.g., Miyake et al., 2000; Sambol et al., 2023). The specific models ran in CFA included: the unity/diversity framework, the nested model of EF, the independent-factor model, and the single-factor model (Miyake et al., 2000; Sambol et al., 2023) for both effectiveness and efficiency independently.

3. Results

3.1. Correlations

Table 3 shows the correlations between expertise and EF effectiveness and efficiency scores for inhibition, shifting, and updating tasks. Expertise was significantly positively correlated with GNGT efficiency, and Colour-Shape Task efficiency. This may suggest the expert advantage in athletes is specific to EF efficiency (i.e., resources used to maintain effectiveness), rather than EF effectiveness (i.e., performance accuracy only). The largest significant correlations were evident between the individual task measures for effectiveness and efficiency (e.g., SST effectiveness and SST efficiency). Additional significant between-task correlations were also found (see Table 3 for specific correlations).

3.2. Confirmatory factor analysis

3.2.1. Effectiveness

All CFA models for EF effectiveness were performed using the Lavaan package (Rosseel, 2012) in RStudio. To assess model fit a series of absolute (i.e., Chi-Square [χ^2]) and relative (i.e., Comparative Fit Index [CFI], Tucker-Lewis Index [TLI], Root Mean Square Error of Approximation [RMSEA], Standardised Root Mean Squared Residual [SRMR], Akaike Information Criterion [AIC]) indices were used and interpreted following the recommendations of Kline (2023). Specifically, χ^2 should be non-significant (Kline, 2023), CFI should be $\geq$ .90, TLI should be $\geq$ .95, RMSEA should be $<$ .08, SRMR should be $<$ .08, and AIC does not require a specific value, but smaller values indicate a more parsimonious and ideal model (Akaike, 1973). Factor loadings greater than .30 were deemed acceptable with values increasingly closer to 1.00 indicating a greater factor loading (Comrey & Lee, 1992). All model fit indices are shown in Table 4.

The independent-factor model showed the poorest absolute and relative fit (see Table 4). This suggested that setting the covariance between latent factors to zero was not appropriate and the latent inhibition, shifting, and updating factors covary. Factor loadings provided mixed support for the independent-factor model (see Fig. 1C). The factor loadings for SST effectiveness loaded excellently on to the inhibition factor, but GNGT effectiveness loaded poorly. For the shifting factor, the Modified Flanker Task effectiveness loaded excellently while the Colour-Shape Task effectiveness loading was fair. Finally, the updating factor did not appear to emerge in this model with both Digit Span Task and 2-Back Task effectiveness loadings below the .30 cut-off. The single-factor model also showed poor absolute and relative fit (with only SRMR acceptable; see Table 4) suggesting a single "common EF" may not be present in athletes. Factor loadings were generally acceptable though and ranged from fair-very good apart from GNGT effectiveness which did not load sufficiently (see Fig. 1D).

The unity/diversity framework of EF showed excellent absolute and relative model fit (see Table 4). This may suggest the original framework where factors are correlated but also independent (i.e., the lower-order model; Miyake et al., 2000) is appropriate for use with athletic samples. The factor loadings for inhibition and shifting factors were sufficient with loadings ranging from fair-very good (see Fig. 1A). As in the independent-factor model, the updating factor was not supported (i.e., Digit Span Task and 2-Back Task effectiveness loadings were below acceptable). The nested model of EF also showed excellent absolute and relative model fit and marginally outperformed the unity/diversity framework of EF model (see Table 4). This may suggest the revised model of Friedman et al. (2008) is more appropriate for athletes.

However, the latent updating factor showed negative variance and the factor loading with "common EF" exceeded 1.00. As a result, modifications were made involving fixing the covariance between the updating and "common EF" factors and fixing the variance of the updating factor to zero. Such modifications did not alter the absolute and relative fit indices (see "Modified Nested Model" in Table 4). However, factor loadings were now appropriate (see Fig. 1B). Colour-Shape Task and Modified Flanker Task effectiveness showed good-very good loadings and the shifting factor loaded on to the "common EF" excellently. The Digit Span and 2-Back Tasks again did not load on to an updating factor and the updating factor did not load suitably on to the "common EF" factor. Finally, SST effectiveness loaded to a fair level on the "common EF" factor and GNGT effectiveness showed a poor-fair loading (see Fig. 1B).

3.2.2. Efficiency

The efficiency models were performed using the Lavaan package (Rosseel, 2012) in RStudio. Model fit was again assessed with absolute (i.e., χ^2) and relative (i.e., CFI, TLI, RMSEA, SRMR, AIC) indices and interpreted following Kline's (2023) recommendations. All model fit indices are shown in Table 5. The independent-factor model showed the poorest absolute and relative fit indices (see Table 5) suggesting that pre-specifying zero correlations between latent factors was not appropriate for EF efficiency outcomes in athletes. Both Colour-Shape and Modified Flanker Task efficiency loaded excellently on to the shifting factor. 2-Back Task efficiency loaded excellently on to the updating factor, but Digit Span Task efficiency loaded poorly. Finally, GNGT efficiency showed good loading on to the inhibition factor, but SST efficiency loaded poorly (see Fig. 2C). The single-factor model also showed poor absolute and relative fit with only the SRMR acceptable (see Table 5). This suggested a single "common EF" may not be suitable for athletes. Factor loadings were generally acceptable and ranged from

Table 2
Mean, standard deviation, skew, and kurtosis for expertise and EF effectiveness and efficiency outcomes.

Variable	Mean(SD)	Skewness	Kurtosis
Expertise	4.44(2.34)	.84	3.38
Go/No-Go Task Effectiveness	22.44(16.73)	−.70	3.29
Go/No-Go Task Efficiency	6.56(5.39)	−1.03	5.69
Stop Signal Task Effectiveness	−7.78(13.99)	−1.21	3.75
Stop Signal Task Efficiency	706.52(113.89)	−2.05	8.50
Backward Digit Span Task Effectiveness	−3.71(8.58)	.82	3.40
Backward Digit Span Task Efficiency	−3.21(10.53)	.77	6.21
2-Back Task Effectiveness	21.14(18.21)	−.46	2.35
2-Back Task Efficiency	2.95(2.72)	−.01	3.36
Colour-Shape Task Effectiveness	37.22(10.57)	−1.18	4.56
Colour-Shape Task Efficiency	4.88(2.10)	.25	2.96
Modified Flanker Task Effectiveness	50.52(28.01)	−2.61	9.78
Modified Flanker Task Efficiency	6.99(4.04)	−2.21	9.25

Note. SD = standard deviation.

Table 3
Correlations between expertise and EF effectiveness and efficiency outcome variables.

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1) Expertise	1.00												
2) Go/No-Go effectiveness	.14	1.00											
3) Go/No-Go efficiency	.19*	.97***	1.00										
4) Stop Signal effectiveness	−.07	.18*	.13	1.00									
5) Stop Signal efficiency	−.03	.12	.11	.50***	1.00								
6) Digit Span effectiveness	.02	.18*	.17*	.20*	.21*	1.00							
7) Digit Span efficiency	.04	.19*	.18*	.20*	.25**	.97***	1.00						
8) 2-Back effectiveness	.05	.23*	.26*	.29***	.22*	.05	.04	1.00					
9) 2-Back efficiency	.12	.23*	.26*	.24**	.18*	.08	.06	.95***	1.00				
10) Colour-Shape effectiveness	.02	.06	.07	.30***	.32***	.39***	.34***	.36***	.34***	1.00			
11) Colour-Shape efficiency	.17*	.05	.09	.16	.28**	.32***	.28**	.38***	.41***	.69***	1.00		
12) Flanker effectiveness	−.01	.06	.11	.13	.08	.22*	.20*	.35***	.31***	.33***	.23**	1.00	
13) Flanker efficiency	.03	.19*	.26**	.19*	.19*	.29***	.26**	.50***	.47***	.45***	.49***	.83***	1.00

Note. $^{*}p < .05$, $^{**}p < .01$, and $^{***}p < .001$.

Table 4
Model fit indices and interpretation criteria for all EF effectiveness models.

Fit Statistic	Unity/ Diversity Framework	Nested Model	Modified Nested Model	Single Model	Independent Model
χ^2	7.60	8.43	8.43	24.87*	83.62*
CFI	.98	.98	.98	.82	.15
TLI	.96	.97	.97	.70	−.41
RMSEA	.05	.04	.04	.12	.25
SRMR	.04	.04	.04	.07	.19
AIC	6402.82	6401.65	6401.65	6414.09	6472.84

Note. $^{*}p < .05$.

fair-very good (Comrey & Lee, 1992; see Fig. 2D).

The unity/diversity framework of EF showed excellent absolute and relative model fit (see Table 5). As a result, it may be that the original model from Miyake et al. (2000; the lower-order model) is suitable for athletes. Examination of the factor loadings suggested that both Colour-Shape and Modified Flanker Task efficiency loaded very good-excellent on the shifting factor and that GNGT and SST efficiency loaded poorly-fairly on the inhibition factor. The updating factor was not supported as all loadings were poor (see Fig. 2A). The absolute and relative fit indices for the nested model of EF were excellent and marginally better than the indices associated with the unity/diversity framework of EF (see Table 5). This result may allude to the nested model of EF being more suitable for use with athletes. However, a negative variance and a factor loading greater than 1.00 suggested some issue with the nested model of EF.

After fixing the covariance between updating and “common EF” factors and setting the variance on the updating factor to be zero, the variance and factor loading issues were removed while absolute and relative fit indices were not altered (see “Modified Nested Model” in Table 5). Colour-Shape and Modified Flanker Task efficiency showed very good-excellent loadings on to the shifting factor and the shifting factor loaded on to the “common EF” factor excellently. Both Digit Span

Table 5
Model fit indices and interpretation criteria for all EF efficiency models.

Fit Statistic	Unity/ Diversity Framework	Nested Model	Modified Nested Model	Single Model	Independent Model
χ^2	8.57	8.60	8.60	18.56*	86.88*
CFI	.98	.99	.99	.91	.30
TLI	.94	.97	.97	.86	−.17.
RMSEA	.06	.04	.04	.09	.26
SRMR	.04	.04	.04	.06	.21
AIC	5258.10	5256.13	5256.13	5262.10	5330.42

Note. $^{*}p < .05$.

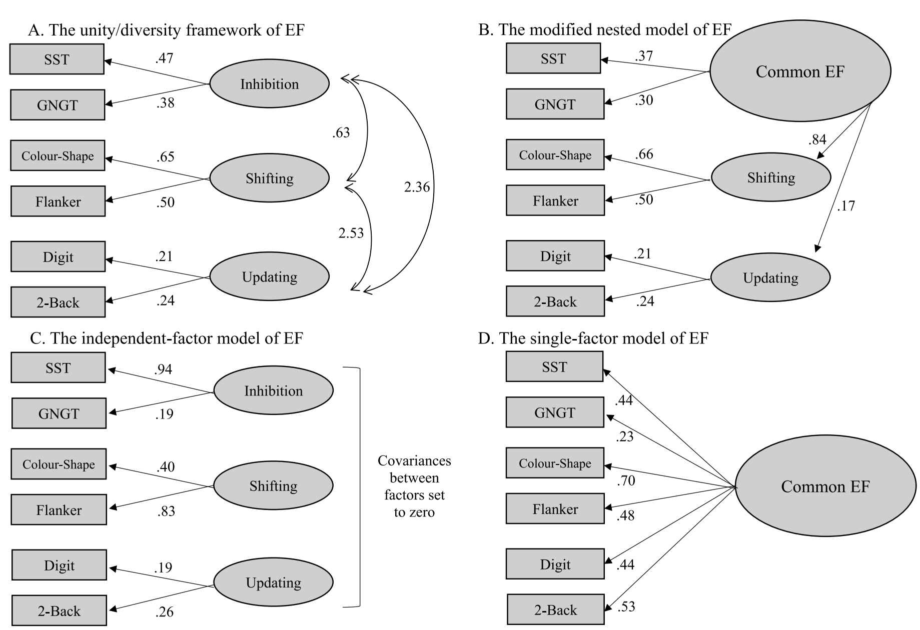

Fig. 1. Shows the factor loadings and latent variances for each EF effectiveness model.

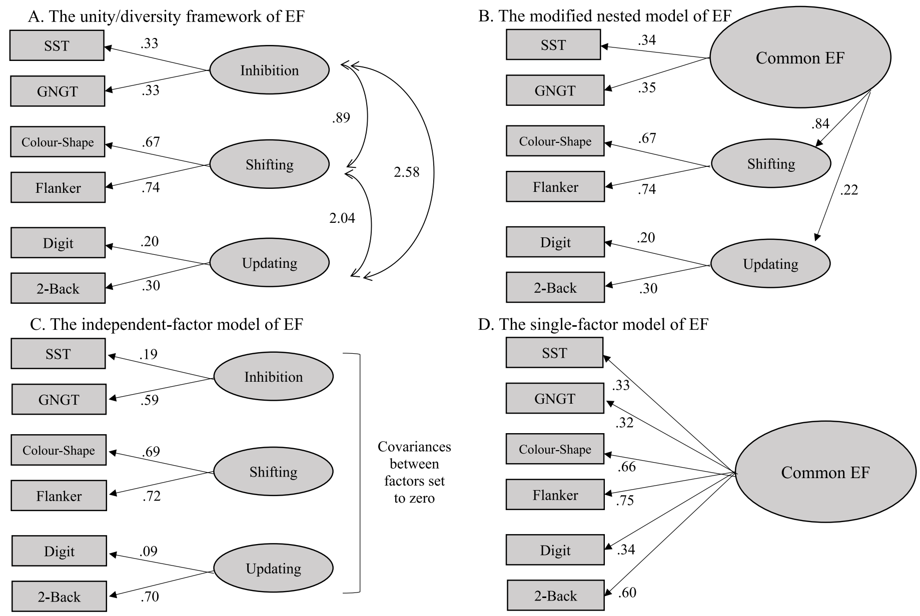

Fig. 2. Shows the factor loadings and latent variances for each EF efficiency model.

and 2-Back efficiency failed to load on to an updating factor and the updating factor did not load on to the "common EF" factor. Finally, SST and GNGT efficiency showed fair loadings for the "common EF" factor (see Fig. 2B).

4. Discussion

The main aim of the present work was to use CFA to understand which theoretical structure of EF (i.e., the unity/diversity framework of EF, the nested model of EF, the independent-factor model of EF, and the single-factor model of EF) was most appropriate in a sample of athletes. Our main hypothesis was partially supported as although the unity/diversity framework of EF was a suitable model, its suitability was surpassed by the nested model of EF. Each theorised EF structure proposes a different degree of association between inhibition, shifting, and updating with previous work supporting the unity/diversity framework of EF and nested model of EF in their target sample (i.e., students). However, athletes are a unique population as regular bouts of submaximal exercise increases oxygenated blood flow within the PFC (Giles et al., 2014) subsequently increasing synaptic alterations in this area. This, coupled with mixed findings on the relevance of certain EFs for athletes (Furley et al., 2023), make it poignant to understand the EF structure in this specific population. For both effectiveness and efficiency, the results of the CFA revealed that the nested model of EF may be the most suitable EF structure for athletes with the unity/diversity framework of EF an acceptable alternative. This is the first step in understanding the EF structure of athletes and future works should examine differences in athlete vs non-athlete groups to better understand the suitability of such EF models.

4.1. Model fit indices

Both the absolute and relative fit indices from the CFA results for effectiveness and efficiency indicated poor model fit for the independent-factor model of EF in the current sample of athletes. This supports previous presumptions (i.e., Friedman et al., 2008; Miyake et al., 2000) and aligns with early cognitive theorists (e.g., Baddeley, 1998). Central to the independent-factor model is the idea that all EFs are completely unique with no shared variance. However, this notion has been consistently challenged. For example, Miyake et al. (2000) argued that EFs often manifest themselves by first impacting, or being impacted by, other cognitive processes suggesting some relation or overlap between EFs. Baddeley (1998) purported that though constructs like working memory can be divided to subcomponents, they are interrelated and not independent and solitary working mechanisms. Furthermore, although Sambol et al. (2023) did not explicitly test the independent-factor model of EF, their analyses revealed a degree of association among EFs (e.g., in the form of a cognitive flexibility factor comprising inhibition and shifting), implying that the assumption of EF independency is inaccurate. Therefore, this present finding adds to the evidence supporting a combined effect and degree of shared responsibility of these EFs in influencing performance on typical EF tasks.

The single-factor model of EF was also a poor fit for the effectiveness and efficiency data in the current sample of athletes. The single-factor model of EF can be considered a somewhat opposing model of the independent-factor model of EF in that there is no distinction between processes but rather a single over-arching construct controlling EFs. This finding aligns with previous research, as extensive investigations into individual differences across EFs have supported a non-unitary explanation in specific populations, including healthy adults (Friedman et al., 2008; Sambol et al., 2023), healthy older adults (Lowe & Rabbitt, 1997), and adults who have suffered brain damage (Burgess et al., 1998) and now, athletes. Interestingly, research typically focuses on a population of interest when assessing EF module structure. It may be that future work wishes to compare module structure between a two distinct populations (in this case athletic and non-athletic) to examine differences. Overall, the rejection of these two models (i.e., independent-factor and single-factor model of EF) was expected and alludes to a more intricate relationship between EFs where they are related, yet distinct as alluded to in previous work (Friedman et al., 2008; Miyake et al., 2000; Sambol et al., 2023).

Pertinent to the current study is the suitability of the nested model and the unity/diversity framework of EF. The nested model of EF emerges as most suitable structural configuration among those examined in this specific athletic population. The absolute and relative fit indices for the nested model of EF were both excellent, aligning with Friedman et al. (2008) and contradicting the findings of Sambol and colleagues (2023). One key difference between these studies were the tasks selected to assess the EFs of interest. One criticism of Friedman et al. (2008) and Miyake et al. (2000) from Sambol and colleagues (2023) was that the EF tasks employed shared very similar methodological processes. This suggests that observed relationships may be attributed to specific methodological skills rather than the underlying domain-general EF (Sambol et al., 2023). It is difficult to say whether the current study is similar to Friedman et al. (2008) since the EF tasks in our study are different to the ones used in previous research (e.g., Friedman et al., 2008; Sambol et al., 2023). We believe the selected tasks assess the same EFs, yet they do not suffer methodological similarity issues, as evidenced by non-perfect correlations between tasks.

The unity/diversity framework of EFs also showed excellent absolute and relative model fit. The strong support for the unity/diversity framework and the similarity in values to the nested model of EF make it difficult to determine which model is superior (though again, the indices marginally favour the nested model of EF). It is not surprising that the fit indices for these models were so close as they are constructed in similar ways. The only difference being that the nested model of EF includes an additional higher order component (i.e., the "common EF"). For more clarity, future research may consider testing the unity/diversity framework and nested model of EF using different EF tasks and indeed, across athlete and non-athlete populations. For example, a group of participants could complete 12 EF tasks (i.e., four per EF). Half of these tasks (i.e., two inhibition, two shifting, and two updating) could be then allocated to constructing the unity/diversity framework of EFs, while the remaining tasks could be employed to construct the nested model of EF. A comparison between these two models could determine the superior model. One consideration with this approach is that the selection of tasks is carefully thought through to avoid the results being influenced by significant differences in task methodology.

4.2. Factor loadings

Despite excellent model fit indices for the nested model of EF the factor loadings were mixed. For both EF effectiveness and efficiency, the Colour-Shape and Modified Flanker Tasks showed good to excellent factor loadings on the shifting factor and were positively significantly correlated. In addition, this latent shifting factor loaded excellently on to the "common EF". This indicates that a separable shifting-specific factor aids shifting task performance, but that this shifting ability is superseded by an overarching "common EF". This may support previous research (i.e., Friedman et al., 2008) which endorses the suitability of the nested model of EF and extend this line of work by demonstrating the relevance of this model among athletes in our sample. Although weaker in magnitude, the factor loadings for the SST and GNGT did reach acceptable levels on to the "common EF" latent factor. As with the shifting factor, inhibition effectiveness and efficiency showed similar values however the efficiency scores showed marginally higher factor loadings on to the "common EF". It may be that time-based variables are more informative in athletic samples, given the time demands often placed upon them (Brimmell et al., 2022).

The factor loadings for the updating tasks were surprising. First, neither the Digit Span nor 2-Back task loaded acceptably on the updating factor. It appears that in the current sample of athletes, performance on these tasks does not stem from the same EFs. However, these tasks were significantly and positively correlated which does allude to some relationship. It may be the case that these tasks require related, yet distinct EFs. Vaughan and colleagues (2021) outlined that working memory, a construct like updating, comprised 'capacity' and 'ability' components. It may be that in athletes, a more nuanced approach to updating is also needed or perhaps performance is dependent of level of athletic expertise, a notion testable through comparison of EF models at multiple expertise levels (e.g., expert vs novice). Second, the updating latent factor did not significantly load onto the "common EF". Initially, this contradicts the nested model of EF. However, this outcome may stem from the lack of meaningful loadings for the updating tasks onto the updating latent factor. This finding would be more unexpected and contradictory if the tasks loaded appropriately on the updating latent factor, but not on the "common EF". Consequently, the unsuitability of the nested model of EF may not be the issue as indicated by our other results. Instead, it could be attributed to an issue with the tasks used to assess updating in athletes. Therefore, future research should consider employing alternative tasks for a more comprehensive examination.

The factor loadings for the unity/diversity framework of EFs were highly similar to the nested model of EF for both effectiveness and efficiency. For example, the same pattern of good-excellent loadings for the Colour-Shape and Modified Flanker tasks on to the shifting factor was found. Marginal differences in loadings between the models with the values in the unity/diversity framework of EF slightly lower than the nested model of EF for performance effectiveness. This result again supports the nested model of EFs over the unity/diversity framework of EFs in the current athletic sample and aligns with the work of Friedman et al. (2008). The lack of acceptable loadings for the Digit Span and 2-Back Tasks on to the updating factor was also found in the unity/diversity framework of EFs. This is not surprising given that the tasks and structural configuration were the same across models. The inhibition factor in the unity/diversity framework of EFs provided mixed findings. Regarding the unity/diversity model of EF, the SST and GNGT loadings were higher for effectiveness but lower for efficiency. Perhaps this alludes to "common EF" being more relevant for efficiency-based measures and inhibition for effectiveness outcomes.

Another finding worthy of discussion is the factor loadings for the single-factor model of EF. Though the model fit indices did not outline the model as a good fit for the current sample, the factor loadings were surprisingly consistent and above the acceptable level. For EF performance effectiveness, all factor loadings were above the acceptable level apart from the GNGT. Most surprisingly though was that the updating tasks (i.e., Digit Span and 2-Back Tasks) both showed fair to good loadings on to the "common EF" latent factor. Overall, this might support a common underlying EF that supports performance on all EF-related tasks. More evidence for this came from the EF performance efficiency factor loadings for the single-factor model of EF. Here, all tasks used to measure EF had acceptable factor loadings (ranging from fair to excellent) onto the "common EF". The factor loadings from both the single-factor model of EF and the nested model of EF do seemingly support a "common EF" is present in athletes and that it may aid performance on EF related tasks.

4.3. Applications for athletes

The defining characteristic in the nested model of EF is the 'common' EF factor (Friedman et al., 2008). The emergence of the nested model of EF as the most suitable in our sample of athletes suggests that athletes may possess this underlying 'common' EF ability. This is a novel finding for research with athletes where typically the focus is on measuring or training specific EFs (e.g., inhibitory control; see Hagyard et al., 2021). Instead, we are suggesting that it may be more fruitful, or at least *as* fruitful, to make the 'common' EF the target of research with athletes. Interestingly, this may align with the recent work of Furley et al. (2023) who outlined current issues with conceptualising EF. Specifically, the 'common' EF is theorised as a generic ability facilitating goal-directed attentional control and efforts to further conceptualise more specific and nuanced processes might be unnecessary (i.e., it's more accurate and simpler to conceptualise EF as a broad goal-directed ability). Therefore, future research may wish to direct training interventions towards improving goal-directed attention in order to see if any subsequent improvement across various EFs emerge. Even if subsequent benefits to EF do not emerge, training goal-directed attention is highly relevant for athletes given that they are often in situations requiring goal-directed behaviour (e.g., selecting a teammate to pass a ball to from a multitude of potential receivers).

The emergence of shifting- and updating-specific factors suggests there is something specific to the shifting and updating tasks, beyond that which is accounted for by the 'common' EF factor (Friedman et al., 2008), within the current sample of athletes. In one of the most state-of-the-art examples to date, Knobel and Lautenbach (2023) replicated the classic *n*-back task within the SoccerBot and found the new measure to be a valid but football-specific method for assessing updating. The present work provides support to such endeavours as we can suggest that there are updating-specific abilities present within athletes over and above the 'common' EF. Interestingly, neither the present work nor the work of Knobel and Lautenbach (2023) can rectify recent issues about whether EFs can predict future sport performance outlined in Kalen et al. (2021). Though sport-specific EF measures may be more fruitful for predicting future performance, whether this is true or not remained untested.

4.4. Limitations

The present work makes a number of novel contributions but is not without limitations. First, the study exclusively employed CFA and not EFA, in contrast to previous research (e.g., Sambol et al., 2023). This approach was taken due to the already substantial number of models established in the literature. The key difference between these two techniques is that CFA restricts the observed variables to manifest on specific latent variables, whereas EFA allows observed variables to load on any or all latent variables. Future research is encouraged to investigate if the recommended model here (i.e., the nested model of EF) replicates when using EFA. On this note, and although typical of research in this area, the present work provides commentary on the suitability of EF models in relation to a single athletic sample. Future work is encouraged to obtain data from both an athletic and non-athletic sample for comparison purposes.

Second, Sambol et al. (2023) outlined that an issue with previous work (e.g., Miyake et al., 2000) was that the EF tasks shared similar methodologies which inflated certain results. It cannot be ruled out here that the tasks do not have some underlying similar methodology. Future work is encouraged to use different tasks and examine if the findings reproduce. One way to address this may be to adopt a similar approach to Sambol et al. (2023) whereby the authors have an explicit aim to utilise EF tasks that assess the same underlying EF but have very different procedural requirements. For example, researchers could select a range of tasks that all measure inhibition but perhaps one requires motor inhibition, one requires cognitive inhibition, and one requires verbal inhibition. In doing so, we could assess the degree to which an underlying inhibition skill is present and not just comment on task-specific inhibition.

5. Conclusion

Research around EF has outlined many potential structures for the lower-order model of EF (i.e., independent-factor model, single-factor model, unity/diversity framework of EF, and the nested model of EF). Given that recent research has called into question these structures (see Sambol et al., 2023) and that no model structure has been tested in a sample of athletes, despite their potential for difference, further cause for investigation was warranted. Although the unity/diversity framework of EF had appropriate model fit and acceptable factor loadings, the nested model of EF (Friedman et al., 2008) marginally outperformed all other models regarding model fit and often factor loadings. Therefore, in athletes it is likely the lower-order model of EF is made up of an underlying "common EF" with a shifting-specific component for both effectiveness and efficiency. Whether this "common EF" has predictive power over future performance remains to be tested.

CRediT authorship contribution statement

Jack Brimmell: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation. **Elizabeth J. Edwards:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Liis Uiga:** Writing – review & editing, Writing – original draft. **Greg Wood:** Writing – review & editing, Writing – original draft, Conceptualization. **Robert S. Vaughan:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization.

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.

Data availability

Links to osf page with code and data throughout

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