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# Expertise-Dependent Effects of Neurofeedback Design During Motor Imagery

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## ABSTRACT

Motor imagery (MI) combined with neurofeedback (NF) is a promising approach to enhance sport performance, yet its effectiveness remains heterogeneous. Athletic expertise emerges as a primary candidate for this heterogeneity, potentially determining how athletes engage with different feedback designs to modulate sensorimotor rhythms (SMRs). Whether explanatory feedback (neural processes) and evaluative feedback (performance magnitude) differentially benefit athletes as a function of expertise remains unknown. We examined these designs across novice, intermediate, and expert basketball athletes imagining free throws across four feedback conditions: no feedback (None), an evaluative target (Evaluative), an explanatory topographic map (Explanatory), or both (Both). While intermediates and experts improved when feedback was present relative to None, novices showed no benefit from feedback presence alone. Crucially, gaze–performance coupling revealed a double dissociation: novice success increased with fixation on explanatory information, whereas expert success increased with fixation on evaluative information. These findings support the implementation of adaptive feedback designs to optimize MI-NF training.

## INTRODUCTION

MI, the mental simulation of movement without overt execution, is widely used to enhance sport performance [1]. By engaging neural networks that substantially overlap with those recruited during actual movement, MI can support skill refinement and motor learning [2,3]. However, MI outcomes are heterogeneous, and expertise is a major contributor to this variability, shaping both behavioural effects and underlying neural recruitment [4,5].

A central distinction concerns MI modality. Visual imagery emphasizes the visual and spatial characteristics of the action from an internal or external perspective [6], whereas kinaesthetic imagery focuses on somatic and proprioceptive sensations, the “feel” of movement [7]. These modalities recruit partially distinct neural substrates: visual MI preferentially engages occipito-parietal regions, whereas kinaesthetic MI more strongly recruits sensorimotor networks [1]. Expertise also affects MI quality: experts typically show greater

temporal congruence between imagined and executed movements, more accurate kinaesthetic representations, and more efficient neural activation patterns consistent with refined internal models [4,5,8–10].

Real-time NF may help address MI variability by providing immediate information about ongoing brain activity [11,12]. In MI settings, electroencephalography (EEG)-based NF can monitor imagery-related signatures such as event-related desynchronisation (ERD) in sensorimotor rhythms (SMR; 12–15 Hz) over motor cortices [13,14]. While NF has shown potential to improve sport performance, its effectiveness depends strongly on methodological rigor and protocol/interface design quality, including compliance with CRED-NF recommendations [15–17]. This suggests that outcomes reflect not only individual traits, but also how feedback information is communicated, interpreted, and used. In motor learning, a well-established distinction separates explanatory feedback (information about the processes driving that performance), from evaluative feedback (information about the magnitude of performance) [18,22]. These two feedback types differ not only in content but in the cognitive demands they place on the learner.

In the context of MI-NF, this distinction maps naturally onto explanatory topographic feedback, which communicates the spatial pattern of neural activity, and evaluative intensity-based feedback, which provides information on SMR modulation magnitude. While their relative utility as a function of expertise remains underexplored in MI-NF contexts, evidence from motor learning suggests that the relevance of each feedback type may shift with skill level [18,22]. Here, we hypothesised that novices would benefit primarily from explanatory feedback as a scaffold for building an internal representation of the target neural state, whereas experts, already possessing stable sensorimotor representations, would benefit most from evaluative feedback as a precise signal to monitor and calibrate their ongoing SMR modulation. To test these hypotheses, novice, intermediate, and expert basketball athletes performed MI of free throws under four feedback conditions: None (no feedback), Explanatory (a simplified topographic map visualising sensorimotor and occipital activity), Evaluative (a unidimensional dynamic target reflecting SMR modulation magnitude), and Both (combined). To dissociate feedback presence effects from usage effects, gaze behaviour was recorded

via eye tracking and integrated into a hybrid generalised linear mixed model (GLMM), enabling trial-by-trial success to be modelled as a function of both feedback condition and fixation duration.

## MATERIALS AND METHODS

**Participants:** Twenty-four right-handed athletes were recruited, though one was excluded due to excessive noise in the recording. The final sample comprised 23 athletes (13 females, 10 males) naive to NF protocols. Participants were categorised into three competitive levels: Novices (n=8;  $23.1 \pm 2.0$  years), Intermediates (n=8;  $26.9 \pm 7.4$  years), and Experts (n=7;  $24.1 \pm 3.7$  years). One participant was excluded due to movement artifacts. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and received a favorable opinion from a national ethics committee (Comité de Protection des Personnes, CPP 2022-A00626-37). All participants signed an informed consent form.

**Procedure:** Following a familiarisation phase involving the physical execution of basketball free throws and a transition to motor imagery (MI), a 2-minute eyes-open resting EEG baseline was recorded. Participants then completed 8 NF runs, counterbalanced across four feedback conditions (2 runs per condition): None (no feedback), Evaluative (target size proportional to SMR-ERD amplitude), Explanatory (cortical mapping of SMR and occipital activity), and Both. Each run consisted of 10 MI trials lasting 10 seconds each (20 trials in total per condition), separated by a 6–7 second inter-trial interval. The entire experimental protocol, encompassing both the baseline recording and the MI-NF runs, was administered using the Neurathletics software (Neurathletics, France).

**Data Acquisition and Processing:** EEG activity was recorded at 250 Hz using an 8-electrode Unicorn Hybrid Black system (mastoid reference)(gTec, Austria). Signals were processed in real-time via OpenViBE (1–100 Hz bandpass, 50 Hz notch, artifact rejection  $> \pm 100 \mu V$ ). Region of Interest (RoI) power was extracted for the SMR rhythm (12–15 Hz; C3, Cz, C4) and occipital activity (8–30 Hz; PO7, Oz, PO8). Channel-wise power was estimated using  $P(t) = \log(1 + x(t)^2)$ . Data were smoothed (1s sliding windows, 0.25s step) and expressed as a temporal percentage variation relative to the baseline to drive the NF interface. Gaze behaviour was tracked using Tobii Pro Glasses 3 (Tobii AB, Sweden) extracting absolute fixation durations on Areas of Interest (AOIs).

**Performance Metrics and Statistical Analyses:** Trial success was defined as a mean decrease in SMR power relative to baseline (ERD  $< 0\%$ ). Occipital activity served a purely informative function. The probability of success for each trial was modeled using a binomial Generalised Linear Mixed Model (GLMM) to assess the impact of visual configurations and their actual usage:  $\text{logit}(P(\text{success})) = \beta_0 + (\text{Level} * \text{Evaluative} * \text{Explanatory}) + (\text{Level} * \text{FixEvaluative}) + (\text{Level} * \text{FixExplanatory}) + (1 | \text{Subject})$ .

Explanatory) + (Level \* FixEvaluative) + (Level \* FixExplanatory) + (1 | Subject).

Fixation durations were nested-median-centered to isolate the usage effect exclusively when feedback was present. Post-hoc analyses (Wald z-tests, Holm correction) evaluated the impact of feedback presence, expertise level differences, and fixation trends (emrends) on trial probability of success.

## RESULTS

**Descriptive Overview of Behavioural Performance and Individual Variability** Fig. 1 and Tab. 1 summarise the participant score (number of successful trials out of 20 per condition). Collapsing across expertise levels, mean scores were  $8.2 \pm 5.1$  in None,  $10.3 \pm 5.9$  in Evaluative,  $10.7 \pm 6.3$  in Explanatory, and  $9.8 \pm 5.5$  in Both, with substantial between-participant variability across feedback conditions and within each expertise group.

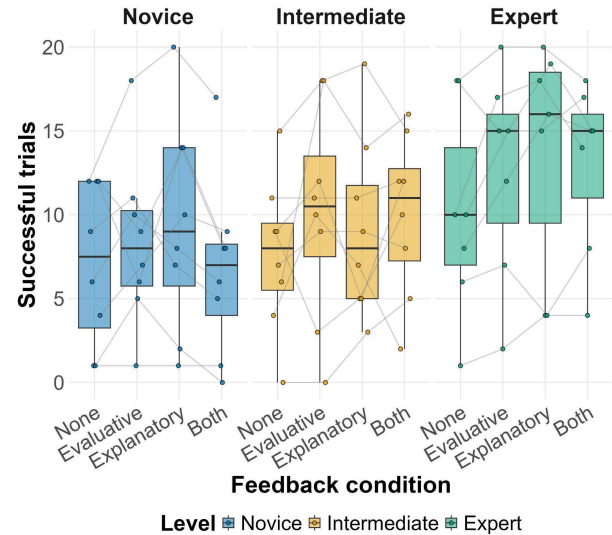


Figure 1: Participant scores across neurofeedback conditions and expertise level.

Table 1: Mean participant scores across neurofeedback conditions and expertise level (Mean  $\pm$  SD).

Feedback	Novice	Intermediate	Expert	All levels
None	$7.1 \pm 4.8$	$7.6 \pm 4.5$	$10.1 \pm 6.2$	$8.2 \pm 5.1$
Evaluative	$8.4 \pm 5.0$	$10.1 \pm 6.4$	$12.6 \pm 6.2$	$10.3 \pm 5.9$
Explanatory	$9.5 \pm 6.4$	$9.1 \pm 5.4$	$13.7 \pm 6.8$	$10.7 \pm 6.3$
Both	$6.8 \pm 5.3$	$10.0 \pm 4.8$	$13.0 \pm 5.1$	$9.8 \pm 5.5$

When examined by expertise level, scores in None condition were  $7.1 \pm 4.8$  for Novices,  $7.6 \pm 4.5$  for Intermediates, and  $10.1 \pm 6.2$  for Experts. When a feedback was present, experts tended to show higher average scores (Evaluative:  $12.6 \pm 6.2$ ; Explanatory:  $13.7 \pm 6.8$ ; Both:  $13.0 \pm 5.1$ ) than novices (Evaluative:

8.4 ± 5.0; Explanatory: 9.5 ± 6.4; Both: 6.8 ± 5.3) and intermediates (Evaluative: 10.1 ± 6.4; Explanatory: 9.1 ± 5.4; Both: 10.0 ± 4.8). Notably, the combined feedback condition did not consistently yield the highest performance within groups (e.g., Novices: Both < Explanatory; Experts: Both slightly < Explanatory).

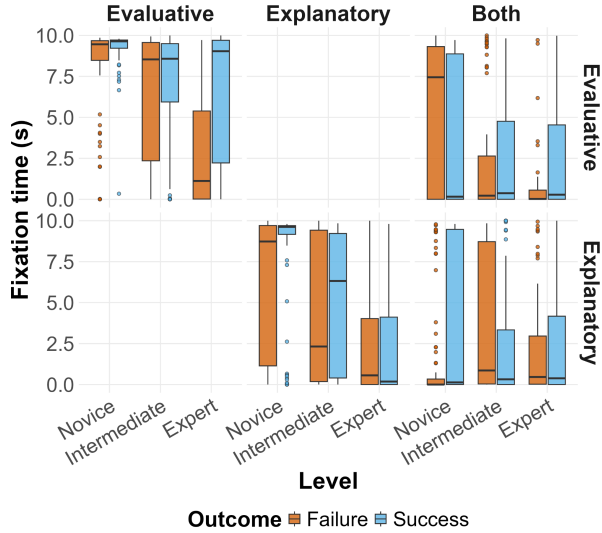


Figure 2: Distribution of fixation duration across feedback condition, trial outcome and expertise level.

Table 2: Mean fixation duration (s) across feedback condition, (Mean ± SD) trial outcome and level of expertise.

Condition	Novice	Intermediate	Expert
Eval - Solo - Fail	8.25 ± 2.70	6.41 ± 3.87	2.88 ± 3.54
Eval - Solo - Succ	9.18 ± 1.30	7.02 ± 3.50	6.61 ± 3.92
Eval - Both - Fail	5.27 ± 4.34	2.25 ± 3.60	0.90 ± 2.13
Eval - Both - Succ	3.84 ± 4.36	2.60 ± 3.61	2.62 ± 3.75
Exp - Solo - Fail	6.31 ± 4.08	4.32 ± 4.28	2.48 ± 3.49
Exp - Solo - Succ	8.14 ± 3.25	5.04 ± 4.02	2.19 ± 3.30
Exp - Both - Fail	1.37 ± 3.04	3.56 ± 4.10	2.25 ± 3.39
Exp - Both - Succ	3.24 ± 4.41	2.26 ± 3.36	2.37 ± 3.49

Fig. 2 and Tab. 2 report fixation durations toward each feedback element during the 10-s trials, within each expertise level and sorted by trial outcome. Two complementary tendencies were apparent. Novices showed longer fixation on the explanatory feedback during successful versus failed trials, both when presented alone (Success: 8.14 ± 3.25 s; Failure: 6.31 ± 4.08 s) and when combined with the evaluative feedback (Success: 3.24 ± 4.41 s; Failure: 1.37 ± 3.04 s). Conversely, experts showed longer fixation on the evaluative feedback during successful versus failed trials, both in the Evaluative-only condition (Success:

6.61 ± 3.92 s; Failure: 2.88 ± 3.54 s) and in Both (Success: 2.62 ± 3.75 s; Failure: 0.90 ± 2.13 s). Experts' fixation on the explanatory feedback remained comparatively low and similar across outcomes (Explanatory-only Success: 2.19 ± 3.30 s; Failure: 2.48 ± 3.49 s). Overall, these descriptive patterns suggest that the mere presence of the different feedback designs, as well as the consequences of actively fixating on them, impact performance differently across expertise levels.

*Statistical Modeling of Success Probability:* To evaluate the impact of feedback presence versus usage on SMR modulation performance during motor imagery across expertise levels, trial-level success probability was modeled using a hybrid binomial GLMM (Tab. 3).

Table 3: Fixed-effect estimates from the hybrid binomial GLMM predicting trial success.

Effect	$\beta$	p
(Intercept)	-0.805	0.090
Intermediate	0.185	0.783
Expert	0.790	0.256
Evaluative	0.304	0.278
Explanatory	-0.043	0.910
Evaluative × Explanatory	-0.470	0.347
Fixation Evaluative	0.012	0.784
Fixation Explanatory	0.106	<b>0.011*</b>
Intermediate × Evaluative	0.319	0.398
Expert × Evaluative	0.584	0.159
Intermediate × Explanatory	0.283	0.545
Expert × Explanatory	1.040	<b>0.031*</b>
Intermediate × Evaluative × Explanatory	0.432	0.498
Expert × Evaluative × Explanatory	-0.005	0.994
Intermediate × Fixation Evaluative	0.063	0.287
Expert × Fixation Evaluative	0.114	0.084
Intermediate × Fixation Explanatory	-0.063	0.254
Expert × Fixation Explanatory	-0.077	0.215

Note: \*  $p < .05$ ; .  $p < .10$ .

This model included the following factors: expertise level (Novice, Intermediate, Expert), feedback presence (Explanatory [yes/no] × Evaluative [yes/no]), fixation time on each feedback type (centered around the median usage). Analysis of the intercept ( $\beta = -0.805$ ,  $p = 0.090$ ) revealed that in the reference condition (Novices, None), the estimated success probability (approximately 0.31) marginally trended below chance levels. Besides,

the mere presence of the feedback interfaces did not significantly improve the performance of novices (Evaluative presence:  $\beta = 0.304$ ,  $p = 0.278$ ; Explanatory presence:  $\beta = -0.043$ ,  $p = 0.910$ ), nor did their combination yield a significant interaction effect ( $\beta = -0.470$ ,  $p = 0.347$ ) Novices' performance rather depended on how NF was used: longer fixation durations on the explanatory feedback significantly improved performance ( $\beta = 0.106$ ,  $p = 0.0115$ ), showing that the behavioural utility of explanatory information in novices emerged with active engagement rather than mere presence.

*Impact of Expertise Level on SMR Modulation Across Feedback Conditions:* As the GLMM was parameterized with Novices in the None condition as the reference level, the reported p-values primarily capture expertise-related differences in SMR modulation performance strictly under the no-feedback condition. To fully map the differential impact of expertise across NF designs, we therefore computed post-hoc estimated marginal means (EMMs) contrasts within each feedback condition at median usage (Tab. 4).

Table 4: Simple effect of expertise level within each feedback condition (Holm-adjusted).

Feedback	Level	$\Delta$ log-odds	p
None	Novice - Intermediate	-0.185	0.783
None	Novice - Expert	-0.790	0.767
None	Intermediate - Expert	-0.605	0.767
Evaluative	Novice - Intermediate	-0.504	0.456
Evaluative	Novice - Expert	-1.374	0.163
Evaluative	Intermediate - Expert	-0.870	0.432
Explanatory	Novice - Intermediate	-0.468	0.523
Explanatory	Novice - Expert	-1.830	<b>0.046*</b>
Explanatory	Intermediate - Expert	-1.363	0.112
Both	Novice - Intermediate	-1.219	0.156
Both	Novice - Expert	-2.409	<b>0.004*</b>
Both	Intermediate - Expert	-1.190	0.156

Note: \*  $p < .05$ ; .  $p < .10$ .

Experts and novices did not differ significantly in None ( $\beta = -0.790$ ,  $p = 0.767$ ) or Evaluative ( $\beta = -1.374$ ,  $p = 0.163$ ). A significant advantage for experts emerged only when explanatory feedback was present, alone ( $\beta = -1.830$ ,  $p = 0.046$ ) and combined with the evaluative feedback ( $\beta = -2.409$ ,  $p = 0.004$ ).

*Impact of Feedback Conditions on SMR Modulation Across Expertise Levels:* We next tested feedback

effects on performance by comparing each feedback condition directly against None within each expertise group, (Tab. 5). This analysis revealed a stratified profile. For Novices, none of the feedback configuration differed from the absence of feedback (Evaluative:  $\beta = 0.304$ ,  $p = 0.833$ ; Explanatory:  $\beta = -0.043$ ,  $p = 0.910$ ; Both:  $\beta = -0.208$ ,  $p = 0.900$ ), reinforcing the conclusion that novice benefit is not driven by the mere presence of a feedback. For Intermediates, performance significantly improved in Evaluative ( $\beta = 0.623$ ,  $p = 0.027$ ) and Both ( $\beta = 0.826$ ,  $p = 0.016$ ), whereas Explanatory alone was not significant ( $\beta = 0.240$ ,  $p = 0.387$ ). For Experts, all three feedback conditions significantly improved performance relative to None (Evaluative:  $\beta = 0.888$ ,  $p = 0.004$ ; Explanatory:  $\beta = 0.998$ ,  $p = 0.002$ ; Both:  $\beta = 1.411$ ,  $p = 0.001$ ). Together, these results show that feedback presence is sufficient to yield robust gains in experts, partially sufficient in intermediates (primarily when evaluative information is present), and insufficient in novices at median usage.

Table 5: Simple effect of feedback condition within each expertise level (Holm-adjusted).

Level	Feedback	$\Delta$ log-odds	p
Novice	Evaluative	0.304	0.833
Novice	Explanatory	-0.043	0.910
Novice	Both	-0.208	0.900
Intermediate	Evaluative	0.623	<b>0.027*</b>
Intermediate	Explanatory	0.240	0.387
Intermediate	Both	0.826	<b>0.016*</b>
Expert	Evaluative	0.888	<b>0.004*</b>
Expert	Explanatory	0.998	<b>0.002*</b>
Expert	Both	1.411	<b>&lt;.001*</b>

Note: \*  $p < .05$ ; .  $p < .10$ .

*Gaze Allocation and SMR-regulation performance:* Beyond the impact of the mere presence of the feedback conditions on performance, which varies according to expertise level, the impact of active gaze allocation, reflecting the distribution of attentional resources, was also investigated. Statistical modeling confirmed a clear double dissociation in gaze-performance coupling across expertise levels. For Novices, fixation duration on the explanatory feedback significantly predicted success ( $\beta = 0.106$ , OR = 1.11,  $p = 0.0115$ ), corresponding to an 11% increase in success odds per additional second, whereas fixation on the evaluative feedback did not ( $\beta = 0.012$ ,  $p = 0.7839$ ). Conversely, for Experts, the pattern was reversed: fixation on the explanatory feedback was not predictive ( $\beta = 0.029$ ,  $p = 0.5321$ ), while fixation on the evaluative feedback

robustly predicted success ( $\beta = 0.126$ ,  $OR = 1.13$ ,  $p = 0.0099$ ), yielding a 13% increase in odds per additional second. Intermediates displayed a transitional profile, with a marginal positive coupling for evaluative feedback fixation ( $\beta = 0.075$ ,  $p = 0.0524$ ) and no significant relationship for explanatory feedback ( $\beta = 0.043$ ,  $p = 0.2398$ ).

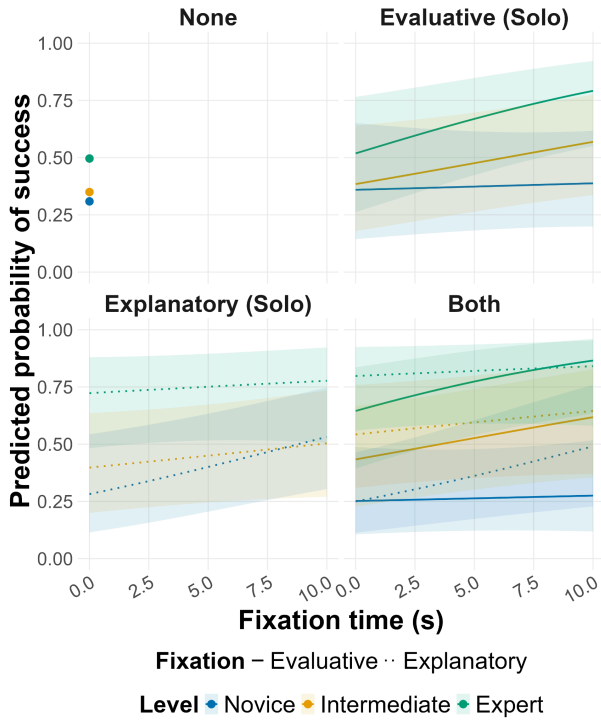


Figure 3: Estimated Probability of Success Based on Evaluative and Explanatory Fixation Times Across Expertise Levels.

Table 6: Fixation slopes by expertise level and feedback

Level	Feedback	Slope ( $\Delta \log\text{-odds} / +1s$ )	p
Novice	Evaluative	0.012	0.784
Novice	Explanatory	0.106	<b>0.011*</b>
Intermediate	Evaluative	0.075	0.052
Intermediate	Explanatory	0.043	0.240
Expert	Evaluative	0.126	<b>0.010*</b>
Expert	Explanatory	0.029	0.532

Note: \*  $p < .05$ ; .  $p < .10$ . No multiple-comparison correction applied.

Overall, the specific visual information stream driving trial success differed fundamentally with expertise: Novices performed better when actively monitoring explanatory topographic information, whereas Experts and Intermediates demonstrated greater success with sustained fixation on evaluative feedback.

## DISCUSSION

The stratified profile described above is consistent with the broader variability of NF responsiveness reported in MI-NF studies [17]. Although all participants were instructed to perform kinaesthetic MI, the present results suggest that novices and experts rely on different informational routes to achieve SMR modulation. Novice athletes, still developing kinaesthetic representations [9], may benefit from explanatory information as a scaffold. This visual support enables them to actively adapt their mental strategies through a trial-and-error process, monitoring the relative involvement of sensorimotor and occipital activity to limit drift toward predominantly visual imagery [1,7,20]. Importantly, while novices spent the most time actively fixating NF overall, they tended to neglect the explanatory feedback when the evaluative feedback was simultaneously present. Because prolonged fixation on the explanatory map is the primary driver of their success, this attentional shift toward the evaluative feedback proved directly detrimental to their ability to self-regulate SMR.

Experts showed the opposite pattern: trial-by-trial success was specifically coupled with monitoring evaluative feedback, while monitoring explanatory feedback did not predict outcome. This is consistent with experts' more stable internal motor representations and the utility of a unidimensional signal for the efficient fine-tuning of an already well-defined sensorimotor strategy during MI [4,5,10,21]. Rather than sustained inspection, the optimal approach for experts seems to involve brief visual sampling of the explanatory feedback for contextual validation, while allocating the majority of their attentional resources to monitoring the evaluative signal.

Intermediates exhibited a transitional profile, consistent with a progressive maturation of kinaesthetic representations. This group represents a critical pivot for adaptive NF as it marks the stage where the feedback design must shift from explanatory to evaluative feedback.

## CONCLUSION

The present study demonstrates that NF design is not a static requirement but a dynamic one that must evolve in alignment with the user's expertise. While novices require isolated explanatory feedback to guide the initial adaptation of their mental strategy, experts optimize SMR modulation through evaluative feedback that allows for the precise fine-tuning of a well-established internal motor model.

This shift in informational needs, from the descriptive "how" for novices to the quantitative "how much" for experts, highlights that the benefit of NF depends on how well the information matches the athlete's current stage of skill acquisition. When NF design is mismatched to the user's level, the information fails to be actionable and may instead act as an attentional

distraction [16]. Future developments should therefore prioritize adaptive interfaces capable of identifying objective markers of user proficiency (such as neural signature or gaze behaviour) to adjust feedback design accordingly. Such dynamic systems would ensure that NF consistently provides optimal support for users learning how to self-regulate specific brain activity.

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#### CONFLICT OF INTERESTS

Certain members of the research team are involved in the development of the Neurathletics application utilized in the present study. The authors declare no further commercial or financial relationships that could be construed as a potential conflict of interest.

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