

Reduced information sharing within the orienting network predicts intelligence in late childhood

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ABSTRACT

Understanding how intelligence emerges from the developing brain remains a central question in developmental cognitive neuroscience. While prior work has linked intelligence to regional activation and structural maturation, less is known about how the efficiency of distributed functional networks contributes to cognitive ability during childhood. We examined 38 children aged 11–14 years as they performed the Attention Network Test (ANT) while undergoing electroencephalography (EEG). Attentional network engagement was characterised using cue-locked event-related potentials (ERPs), frontal midline theta power during conflict processing, and weighted Symbolic Mutual Information (wSMI) to quantify nonlinear information sharing across distributed networks. Canonical electrophysiological signatures of alerting, orienting, and conflict processing were robustly replicated. However, only distributed nonlinear connectivity within the orienting network predicted Full-Scale IQ (FS-IQ). Specifically, reduced information sharing during spatial orienting was associated with higher intelligence scores, whereas local ERP and theta measures showed no reliable associations. These findings suggest that intelligence in late childhood is linked not to greater neural activation, but to more efficient network-level coordination within task-relevant attentional systems. Our results extend the neural efficiency hypothesis into a developmental framework and highlight nonlinear connectivity as a sensitive marker of cognitive maturation.

1. Introduction

Understanding how intelligence emerges from the developing brain remains a central challenge in developmental cognitive neuroscience. Psychometric approaches have traditionally defined intelligence in terms of performance on standardized test batteries (Van der Maas et al., 2014; Wechsler et al., 2008; Roid and Pomplun, 2012), whereas contemporary perspectives increasingly emphasize its neural implementation within distributed brain networks (Hilger et al., 2017a; Colom et al., 2022). In this view, individual differences in cognitive ability reflect not only local neuroanatomical properties (Luders et al.,

2009; Basten et al., 2015) but also the efficiency with which large-scale systems coordinate information processing to support adaptive behaviour (Hilger et al., 2017b; Langer et al., 2012; Haier, 2016; Lanfranco et al., 2022; Lanfranco et al., 2024).

Developmental research indicates that cognitive maturation is accompanied by progressive reorganization of functional brain networks. Across late childhood and early adolescence, frontoparietal systems are refined in ways that increase the segregation of specialized networks while supporting efficient integration among task-relevant nodes (Colom et al., 2022; Gopalan et al., 2019). Longitudinal work further indicates that the development of cognitive capacity is

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associated with functional and structural changes in frontoparietal and frontostriatal systems, particularly in relation to working memory (Darki and Klingberg, 2014). These developmental transitions are thought to underlie improvements in executive control, attentional allocation, and flexible cognition, abilities closely linked to general intelligence (Hilger et al., 2017a; Xiao et al., 2016).

A tractable way to examine how distributed networks support cognitive efficiency during development is through attentional control. The Attentional Network Task (ANT) (Fan et al., 2002) dissociates three partially independent systems: alerting (maintaining readiness), orienting (selectively allocating spatial attention), and executive control (conflict resolution) (Petersen and Posner, 2012). Each network recruits distinct but interacting cortical and subcortical circuits (Petersen and Posner, 2012; Fan et al., 2005, 2007a), providing an experimentally controlled framework to probe network-specific engagement and maturation (Fig. 1).

Electroencephalography (EEG) offers millisecond resolution to capture both local neural responses and distributed coordination during attentional processing (Fan et al., 2007b; Neuhaus et al., 2010; Michel and He, 2019; Canales-Johnson et al., 2021). Cue-locked event-related potentials (ERPs) index preparatory and sensory processing dynamics associated with alerting and orienting (Gopalan et al., 2019; Neuhaus et al., 2010; Kustubayeva et al., 2022; Lanfranco et al., 2021), while frontal midline theta oscillations provide a robust marker of executive control and conflict monitoring (Cohen and Donner, 2013; Cavanagh and Frank, 2014; Canales-Johnson et al., 2020a; Avancini et al., 2024).

However, these univariate measures primarily capture local amplitude or power changes, whereas multivariate approaches can reveal condition-related information distributed across electrodes that may not be apparent in conventional ERP measures (Lanfranco et al., 2024). Developmental and network-based accounts of intelligence instead predict that individual differences may partly arise from how efficiently distributed systems exchange information during task engagement (Hilger et al., 2017b; Langer et al., 2012; Haier, 2016).

Network neuroscience frameworks propose that higher cognitive

ability may be associated with more selective, economical communication between key nodes rather than globally increased connectivity (Hilger et al., 2017b; Langer et al., 2012; Lord et al., 2013). In developmental populations, this may manifest as reduced redundant coupling alongside targeted integration within task-relevant circuits (Colom et al., 2022; Gopalan et al., 2019). Crucially, transient and non-stationary coupling may be especially prominent during development, motivating the use of measures that can capture complex dependencies beyond phase-locked synchronisation (Bonita et al., 2014; Imperatori et al., 2019; Vinck et al., 2023; Vinck et al., 2025; Lanfranco et al., 2024; Canales-Johnson et al., 2021).

Information-theoretic approaches quantify statistical dependencies in neural signals without assuming linearity or stable synchrony, and have been increasingly used to study distributed neural processing (Canales-Johnson et al., 2026; Roberts et al., 2026; Gelens et al., 2024; Canales-Johnson et al., 2023; Lewis-Healey et al., 2024; Potash et al., 2025; Olivares et al., 2025; Blume et al., 2026; Chandia-Jorquera et al., 2026; Chidichimo et al., 2025; Santamaria et al., 2025). Weighted Symbolic Mutual Information (wSMI) is a robust method to estimate nonlinear information sharing between EEG channels while reducing spurious coupling due to common sources (Imperatori et al., 2019; King et al., 2013; Sitt et al., 2014; Canales-Johnson et al., 2020b). By transforming continuous signals into symbolic sequences and quantifying non-random joint fluctuations, wSMI can detect interaction patterns that linear metrics may miss. Our primary interest was not oscillatory synchronisation per se, but the integrative processes through which distributed neural populations jointly combine information during attentional processing. We therefore selected wSMI because it captures nonlinear statistical dependencies that may be missed by canonical functional connectivity measures (Vinck et al., 2023; Schneider et al., 2021; Dowdall and Vinck, 2023), which are restricted primarily to frequency-specific linear phase relationships (Imperatori et al., 2019; King et al., 2013).

Here, we examined whether intelligence in late childhood is associated with the efficiency of information sharing within attentional

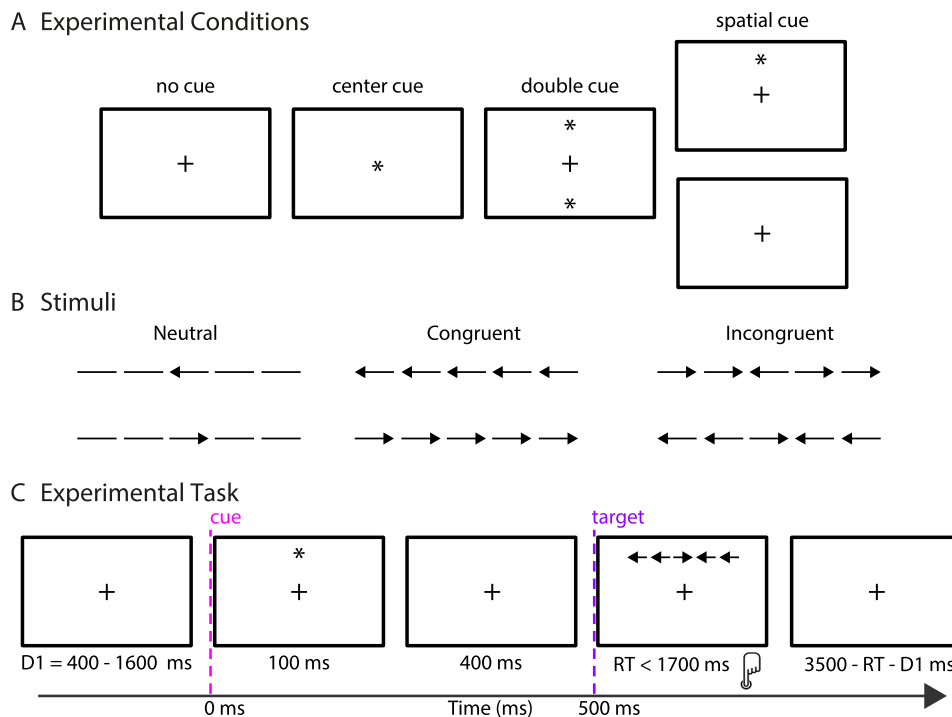


Fig. 1. Experimental design of the Attentional Network Task (ANT). (A) Cue conditions: no cue, center cue, double cue, and spatial cue. (B) Target types: neutral, congruent, and incongruent stimuli. (C) Trial timeline: fixation, cue (100 ms), delay (400 ms), target (max 1700 ms), and response. The inter-trial interval is adjusted based on the reaction time (RT), ensuring a total trial duration of 3500 ms minus the reaction time and initial delay (D1).

networks. Using EEG during the ANT in 11–14-year-old children, we combined ERP indices of cue processing, frontal midline theta as an index of conflict processing, and wSMI to quantify distributed connectivity. We tested the hypothesis that higher Full-Scale IQ (FS-IQ; WISC) (Ramírez and Rosas, 2007) would be associated with more efficient, potentially reduced distributed information sharing within task-relevant networks, consistent with maturation-related optimisation of neural coordination (Hilger et al., 2017b; Langer et al., 2012).

2. Results

2.1. Attentional network task performance

We first examined behavioural performance to confirm robust engagement of the attentional networks in this developmental cohort.

A repeated-measures ANOVA revealed a significant main effect of cue condition on reaction times ($F(3,111) = 148, p < 0.001, \eta_p^2 = 0.800$), indicating reliable modulation of performance by preparatory cues. Holm-corrected post hoc comparisons showed that responses in the no-cue (NC) condition were significantly slower than in the central-cue (CC; $M_{diff} = -39.57$ ms, $t(111) = -10.44, p < 0.001$), double-cue (DC; $M_{diff} = -52.50$ ms, $t(111) = -13.85, p < 0.001$), and spatial-cue (SC; $M_{diff} = -78.10$ ms, $t(111) = -20.60, p < 0.001$) conditions. Double cues yielded significantly faster responses than central cues ($M_{diff} = 12.93$ ms, $t(111) = 3.41, p = 0.005$), and spatial cues were faster than both central cues ($M_{diff} = 38.63$ ms, $t(111) = 10.19, p < 0.001$) and double cues ($M_{diff} = 25.59$ ms, $t(111) = 6.75, p < 0.001$), replicating canonical alerting and orienting benefits in the ANT (Fan et al., 2002, 2007b; Neuhaus et al., 2010).

Conflict processing was also robust. A repeated-measures ANOVA revealed a significant main effect of congruency ($F(2,74) = 260.67, p < 0.001, \eta_p^2 = 0.876$). Incongruent trials produced significantly slower responses than congruent trials ($M_{diff} = 88.64$ ms, $t(37) = 19.24, p < 0.001$) and neutral trials ($M_{diff} = 93.34$ ms, $t(37) = 20.26, p < 0.001$). Congruent and neutral trials did not differ reliably, confirming a selective conflict cost consistent with prior ANT work (Fan et al., 2002; Neuhaus et al., 2010).

When examining computed network scores, a significant main effect of attentional network was observed ($F(2,74) = 42.33, p < 0.001, \eta_p^2 = 0.534$). Conflict scores ($M = 88.6$ ms, $SD = 28.8$) were significantly larger than alerting scores ($M = 52.5$ ms, $SD = 24.9$; $M_{diff} = 36.13$ ms, $t(74) = 6.43, p < 0.001$) and orienting scores ($M = 38.5$ ms, $SD = 20.5$; $M_{diff} = 50.11$ ms, $t(74) = 8.92, p < 0.001$), and alerting scores were larger than orienting scores ($M_{diff} = 13.98$ ms, $t(74) = 2.49, p = 0.015$). Together, these results confirm reliable engagement of alerting, orienting, and conflict networks in this age range (Fig. 2) (Fan et al., 2002; Petersen and Posner, 2012).

2.2. Cue-locked event-related potentials

We next examined cue-locked ERPs to characterize neural dynamics associated with alerting and orienting across the cue–target interval (Gopalan et al., 2019; Neuhaus et al., 2010; Kustubayeva et al., 2022).

For the orienting network (SC vs. CC), cluster-based permutation testing identified a significant posterior spatiotemporal cluster extending from 0.36 to 0.80 s following cue onset ($p < 0.001$), peaking at 0.621 s. Spatial cues elicited larger amplitudes relative to central cues within this window. Because this cluster extended beyond target onset at 0.50 s, it likely reflects a combination of spatially selective preparation and early target-related processing. The topographic distribution of this cluster was maximal over posterior electrodes, consistent with enhanced visual-spatial preparatory processing observed in prior ANT ERP studies (Neuhaus et al., 2010).

For the alerting network (DC vs. NC), a significant central-parietal cluster was observed from 0.22 to 0.79 s post-cue ($p < 0.001$), peaking

Behavioral results

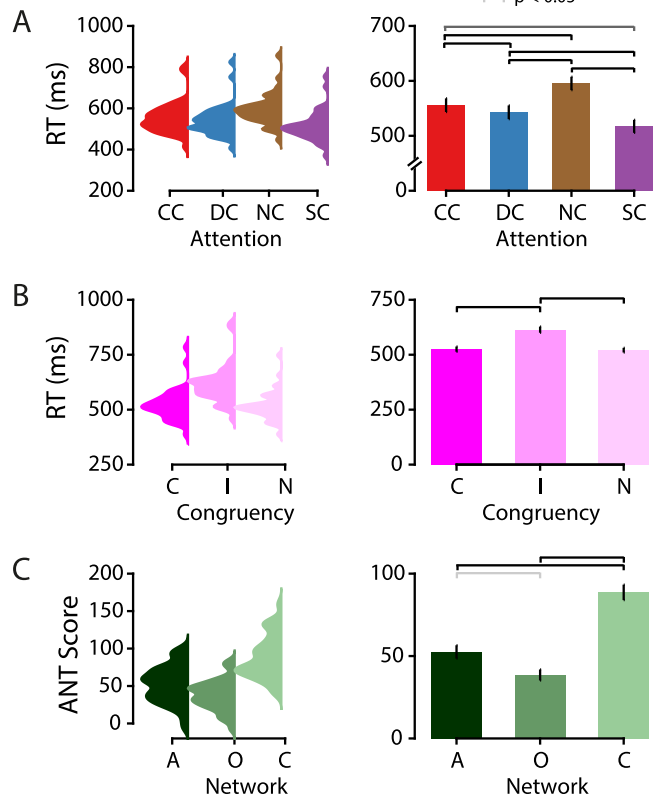


Fig. 2. Behavioural performance in the Attentional Network Task (ANT). (A) Cueing effects on reaction times (RTs) across four cue conditions: central cue (CC), double cue (DC), no cue (NC), and spatial cue (SC). A repeated measures ANOVA revealed a main effect of cue condition ($F(3,111) = 148, p < 0.001, \eta_p^2 = 0.800$), with SC producing the fastest responses and NC the slowest. Post hoc Holm tests confirmed all reported pairwise differences. (B) Conflict effects on RTs for congruent (C), incongruent (I), and neutral (N) stimuli. A significant main effect of congruency ($F(2,74) = 260.67, p < 0.001, \eta_p^2 = 0.876$) indicated slower responses for incongruent than for congruent and neutral trials, with no significant difference between congruent and neutral. (C) Attentional network scores (alerting, orienting, conflict) were computed from correct trials. A main effect of network ($F(2,74) = 42.33, p < 0.001, \eta_p^2 = 0.534$) showed that conflict scores were significantly larger than alerting and orienting scores, and that alerting scores were larger than orienting scores (Holm-corrected pairwise comparisons, all $p < 0.05$). Positive values indicate larger cueing benefits (alerting, orienting) or greater interference (conflict).

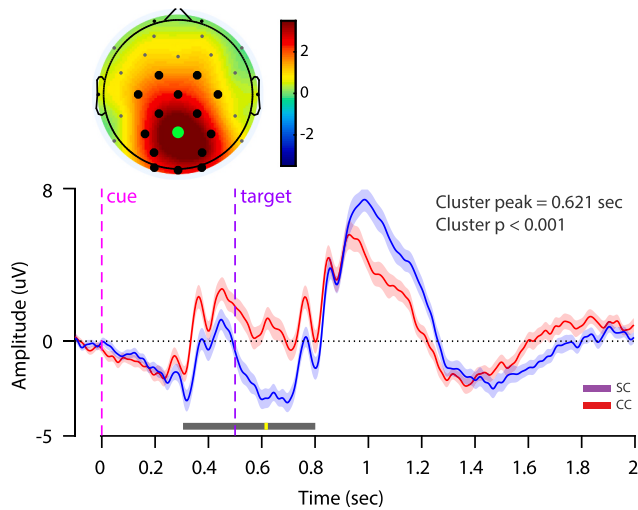
at 0.348 s. Double cues produced greater positivity relative to no-cue trials. As this cluster also extended beyond target onset, the effect likely encompasses both increased preparatory readiness and early target-evoked processing. The spatial distribution was centered over central and parietal regions, consistent with heightened preparatory readiness and prior electrophysiological work on alerting cues (Petersen and Posner, 2012; Neuhaus et al., 2010).

These ERP findings confirm that cue manipulations engaged distinct mechanisms in posterior and centroparietal networks, spanning both cue-related preparation and early target-related processing (Fig. 3) (Fan et al., 2007b; Neuhaus et al., 2010).

2.3. Time–frequency dynamics of conflict processing

To examine executive control mechanisms in the time–frequency domain, we contrasted incongruent and congruent trials. Based on prior work linking frontal midline theta to conflict monitoring and control (Cohen and Donner, 2013; Cavanagh and Frank, 2014; Nigbur et al.,

A ERP: Orienting network (SC - CC)



B ERP: Alerting network (DC - NC)

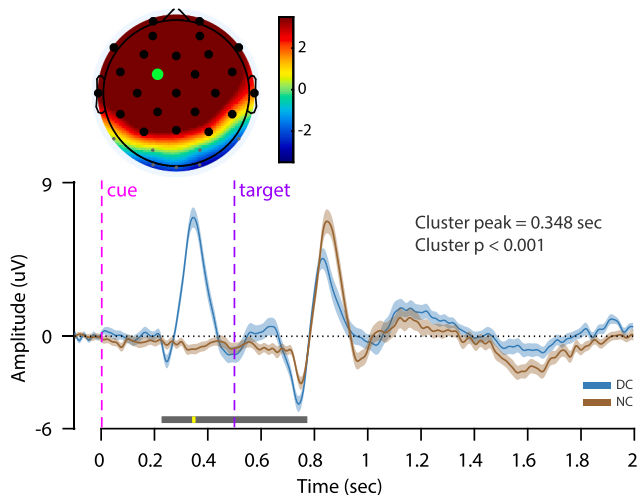


Fig. 3. Cue-locked event-related potentials (ERPs) for the orienting and alerting networks in the ANT. (A) Orienting network: SC (blue) vs. CC (red) trials. A cluster-based permutation test revealed a significant posterior spatio-temporal cluster from 0.36 to 0.80 s post-cue ($p < 0.001$), with SC eliciting higher amplitudes. (B) Alerting network: DC (blue) vs. NC (brown) trials. A significant central-parietal cluster from 0.22 to 0.79 s post-cue ($p < 0.001$) was observed, with DC producing greater positivity. Topographic maps display scalp regions contributing to the significant clusters. Dashed purple lines mark cue and target onsets. Both significant clusters extended beyond target onset at 500 ms and therefore encompass neural activity associated with both cue-related preparation and early target processing.

2012), we tested whether incongruent trials elicited increased theta-band power.

Cluster-based permutation testing revealed significantly greater medial-frontal theta-band power for incongruent trials (cluster $p < 0.001$), spanning 3–14 Hz and 0.8–2.0 s following cue onset. The significant cluster encompassed canonical frontal midline theta frequencies and time windows associated with conflict monitoring (Cohen and Donner, 2013; Cavanagh and Frank, 2014; Jiang et al., 2015; Canales-Johnson et al., 2021). This effect confirms reliable engagement of conflict-related oscillatory dynamics and defines the time–frequency window subsequently used for connectivity analyses (Fig. 4).

2.4. Neural information sharing and intelligence

We next tested whether neural indices of attentional processing predicted individual differences in FS-IQ.

Multiple regression analyses were conducted separately for distributed connectivity (wSMI) and univariate measures (ERP amplitudes and theta power). In the functional connectivity model ($R^2 = 0.283$, $F(3,34) = 4.47$, $p = 0.009$), only orienting-network wSMI significantly predicted FS-IQ ($\beta = -0.413$, 95% CI $[-0.710, -0.117]$, $t = -2.83$, $p = 0.008$; unstandardized $B = -1102.5$). Conflict-network wSMI showed a non-significant association ($\beta = -0.287$, 95% CI $[-0.589, 0.014]$, $t = -1.94$, $p = 0.061$; $B = -835.2$), and alerting-network wSMI did not predict FS-IQ ($\beta = 0.090$, 95% CI $[-0.211, 0.391]$, $t = 0.61$, $p = 0.549$; $B = 219.7$). Influence diagnostics indicated that these associations were not driven by outlying observations. No data point exceeded conventional Cook's distance thresholds (maximum $D = 0.21$), and excluding the two most influential observations ($D > 4/n$) strengthened rather than weakened the orienting effect ($\beta = -0.47$, $t = -3.00$, $p = 0.005$; $r = -0.52$, $p = 0.001$).

In contrast, the univariate model ($R^2 = 0.147$, $F(3,34) = 1.95$, $p = 0.140$) was not significant at the model level, and no univariate predictor survived correction for multiple comparisons (orienting ERP: $\beta = 0.371$, 95% CI $[0.027, 0.715]$, $p = 0.035$ uncorrected, $p = 0.106$ Holm-corrected; alerting ERP: $\beta = -0.210$, $p = 0.226$; conflict theta: $\beta = 0.192$, $p = 0.240$).

To test directly whether the orienting ERP carried intelligence-related information beyond distributed connectivity, we compared the two orienting measures within a single model. Orienting-network ERP amplitude alone was not significantly associated with FS-IQ ($r = 0.29$, $p = 0.082$), and the two orienting measures were correlated ($r = -0.48$, $p = 0.002$). When entered together, orienting-network wSMI remained a significant predictor of FS-IQ ($\beta = -0.377$, 95% CI $[-0.728, -0.026]$, $t = -2.18$, $p = 0.036$; $\Delta R^2 = 0.110$ beyond ERP amplitude), whereas ERP amplitude explained no additional variance beyond wSMI ($\beta = 0.106$, $p = 0.544$; $\Delta R^2 = 0.009$). Intelligence-related variance in the orienting network was therefore carried specifically by distributed information sharing rather than by local response amplitude.

A Pearson correlation confirmed a significant negative association between orienting-network wSMI and FS-IQ ($r = -0.43$, $p = 0.01$), indicating that lower distributed nonlinear information sharing during spatial orienting was associated with higher intelligence (Fig. 5). These results indicate that, in this sample, intelligence-related variance was explained specifically by distributed nonlinear information sharing during orienting, rather than by local ERP or oscillatory power indices (Imperator et al., 2019; King et al., 2013).

Because reaction time (RT) is a well-established correlate of intelligence (Der et al., 2017), we additionally tested whether the wSMI–FS-IQ association was reducible to processing speed. Mean RT (averaged across cue conditions, correct trials) did not significantly predict FS-IQ ($r = -0.17$, $p = 0.31$; $\beta = -0.168$, $R^2 = 0.028$, $F(1,36) = 1.05$, $p = 0.313$). In a hierarchical regression, orienting-network wSMI explained significant additional variance in FS-IQ beyond RT ($\Delta R^2 = 0.163$, $F\text{-change}(1,35) = 7.03$, $p = 0.012$), remaining a significant predictor ($\beta = -0.411$, 95% CI $[-0.725, -0.096]$, $t = -2.65$, $p = 0.012$) while RT was not ($\beta = -0.090$, $p = 0.563$). The same held when all three network wSMI predictors were added jointly ($\Delta R^2 = 0.268$, $F\text{-change}(3, 33) = 4.18$, $p = 0.013$). Thus, distributed information sharing contributed to intelligence-related variance over and above behavioural speed.

3. Discussion

This study examined how neural efficiency within attentional networks relates to intelligence during late childhood. While behavioural performance and canonical electrophysiological markers replicated established ANT effects (Fan et al., 2002, 2007b; Neuhaus et al., 2010), only distributed nonlinear connectivity within the orienting network

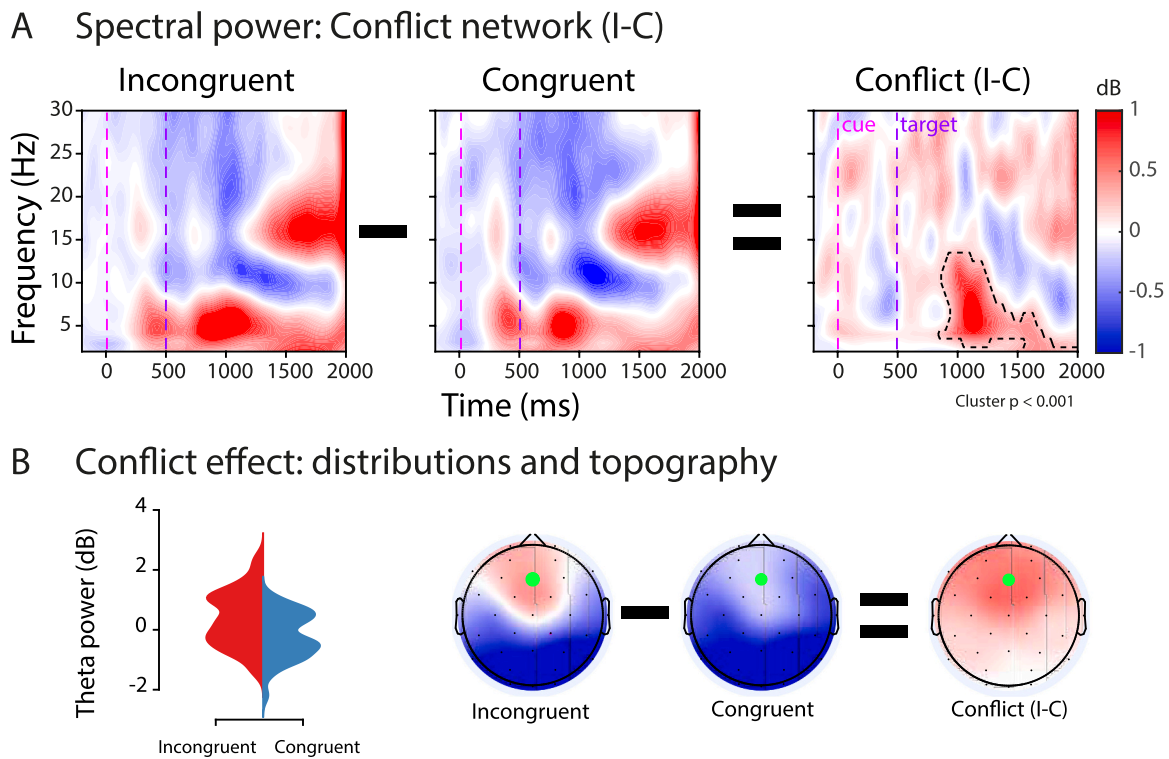


Fig. 4. Theta-band power differences between incongruent and congruent trials in the conflict network. (A) Time–frequency representations of baseline-corrected power for incongruent and congruent trials, and their difference (incongruent minus congruent). Vertical dashed lines mark cue and target onsets. The black dashed contour outlines the significant cluster identified by the cluster-based permutation test. Values are in dB relative to baseline. (B) Frontal-midline theta power (4–9 Hz, averaged over the significant time window) for incongruent and congruent trials. Violin plots show higher theta power for incongruent than congruent trials. Scalp maps display the condition means and their difference, with the green dot marking the frontal-midline electrode used for extraction.

predicted Full-Scale IQ (FS-IQ). Specifically, higher intelligence was associated with reduced weighted Symbolic Mutual Information (wSMI) during spatial cueing, consistent with models linking intelligence to efficient network functioning (Hilger et al., 2017b; Langer et al., 2012; Haier, 2016).

Cue-locked ERPs and frontal midline theta confirmed robust engagement of the three attentional networks. Spatial cues enhanced posterior activity spanning the preparatory and early target-processing periods, alerting cues increased centroparietal activity across the cue–target interval, and incongruent trials elicited elevated frontal theta power (Neuhaus et al., 2010; Cohen and Donner, 2013; Cavanagh and Frank, 2014). These findings validate the task implementation and replicate known electrophysiological signatures of attentional processing in children and adolescents (Gopalan et al., 2019; Kustubayeva et al., 2022; Rueda et al., 2016).

However, these local measures did not reliably explain individual differences in intelligence, and when local and distributed orienting measures were compared directly, orienting-network wSMI predicted FS-IQ beyond ERP amplitude whereas the ERP contributed no unique variance. Intelligence was thus linked specifically to distributed connectivity within the orienting network. This dissociation suggests that in late childhood, cognitive ability may depend less on the magnitude of local neural responses and more on the efficiency of network-level coordination (Hilger et al., 2017b; Haier, 2016).

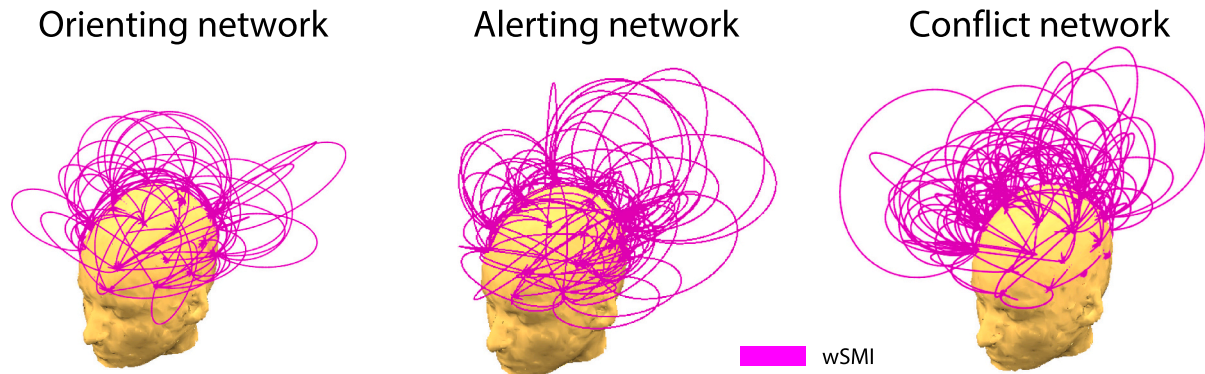
The orienting network comprises dorsal frontoparietal structures including the superior parietal lobule, intraparietal sulcus, and frontal eye fields, along with subcortical regions such as the pulvinar and superior colliculus (Petersen and Posner, 2012; Fan et al., 2005). These regions support spatial prioritization and top-down facilitation of visual processing (Parks and Madden, 2013). The negative association between wSMI and intelligence suggests that higher-IQ children exhibit less diffuse information exchange during spatial orienting. Within a

developmental framework, this pattern likely reflects maturation-related optimisation rather than reduced integration: as networks refine, redundant or non-essential interactions may be reduced, resulting in more selective communication among core nodes and lower distributed information sharing at the scalp level (Colom et al., 2022; Hilger et al., 2017b; Langer et al., 2012).

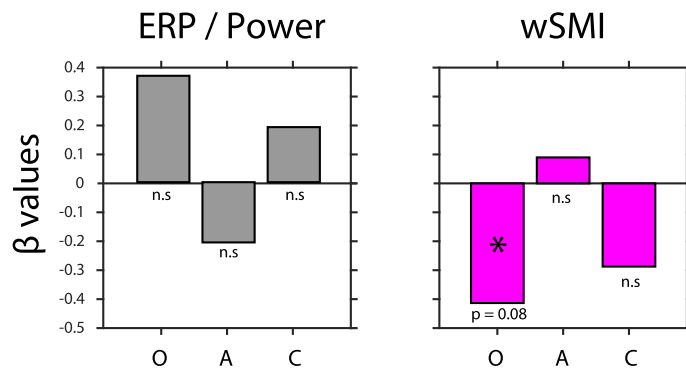
This interpretation aligns with the neural efficiency hypothesis but extends it into a developmental context. Rather than reflecting globally reduced activation, efficiency here appears as reduced distributed nonlinear coupling during a task that requires precise spatial allocation of attention. The effect's specificity to the orienting network suggests that spatial attention may be particularly sensitive to individual differences in frontoparietal network maturation during this developmental window (Gopalan et al., 2019). One mechanistic possibility is that orienting efficiency relates to tighter coupling between covert attention and oculomotor control. The frontal eye fields are closely linked to gaze control and saccadic planning, and spatial attention shifts towards saccade goals during movement preparation (Awh et al., 2006). Pre-saccadic attention shifts can enhance visual acuity and facilitate the transition from peripheral to foveal processing (Rolfs and Carrasco, 2012; Kwak et al., 2023; Li et al., 2021). Although we did not record eye movements, reduced orienting-network wSMI in higher-IQ children may reflect more targeted routing of information between key dorsal frontoparietal hubs while minimizing non-essential cross-network communication (Hilger et al., 2017b; Langer et al., 2012).

The association between orienting-network wSMI and intelligence was not reducible to behavioural processing speed. Reaction time, a robust correlate of intelligence in larger samples (Der et al., 2017), did not significantly predict FS-IQ here, and orienting-network wSMI explained significant variance in FS-IQ beyond RT. This specificity supports the interpretation that the effect reflects the efficiency of neural network coordination rather than a general speed factor.

A Information sharing results



B Multiple regressions



C Simple regression

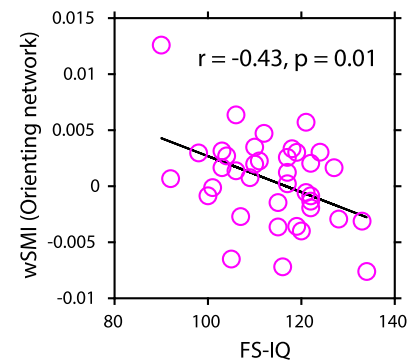


Fig. 5. Relationship between distributed information sharing (wSMI) and Full-Scale IQ (FS-IQ) across attentional networks. (A) Theta-band (4–9 Hz) distributed information sharing patterns (wSMI) across the Orienting, Alerting, and Conflict networks, illustrating joint non-random fluctuations between electrode pairs (magenta lines). (B) Standardized β coefficients from separate regression models for each attentional network, using ERP/theta metrics and wSMI to predict Full-Scale IQ (FS-IQ). In the connectivity model ($R^2 = 0.283$, $p = 0.009$), only orienting-network wSMI significantly predicted FS-IQ ($\beta = -0.413$, $p = 0.008$). (C) Scatter plot of FS-IQ versus wSMI in the Orienting network, the only network where distributed information sharing significantly predicted intelligence ($r = -0.43$, $p = 0.01$).

Our findings can also be situated within developmental accounts of large-scale network reorganization. Across late childhood and adolescence, functional brain networks shift from predominantly local, diffuse connectivity toward more selective and integrated long-range coupling, a refinement that supports increasingly efficient cognition (Fair et al., 2009; Marek et al., 2015; Grayson and Fair, 2017). The dorsal frontoparietal circuitry supporting spatial orienting shows protracted maturation across precisely the age range studied here (Konrad et al., 2005; Rueda et al., 2004; Klingberg, 2014). Within this framework, the negative association between orienting-network wSMI and FS-IQ is consistent with a maturational-refinement account, in which children further along this trajectory may exhibit less redundant distributed information sharing within the orienting network together with higher psychometric intelligence. We emphasize that our cross-sectional design tests a between-person association rather than developmental change itself; longitudinal work is needed to test whether within-person reductions in distributed orienting-network information sharing track gains in cognitive ability.

A key contribution of this work is the use of nonlinear information sharing to capture distributed coordination. More broadly, emerging information-theoretic frameworks aim to characterise not only the amount of shared information but also its relational structure, including redundancy and synergy across behavioural measures and distributed neural populations (Lanfranco, 2026; Canales-Johnson et al., 2026). Traditional linear connectivity metrics (e.g., coherence, correlation) are most sensitive to stationary, linear dependencies and sustained

synchronisation (Bonita et al., 2014). In contrast, cognitive control and attentional allocation can involve transient, non-stationary, and nonlinear interactions that may be overlooked by linear measures (Lord et al., 2013; Parks and Madden, 2013). wSMI is well-suited to detect such interactions by quantifying non-random shared information between symbolized EEG time series while reducing spurious coupling from common sources (Imperator et al., 2019; King et al., 2013). This may be particularly relevant in developmental cohorts, where coupling can be intermittent and dynamically reconfigured (Gopalan et al., 2019; Vinck et al., 2023).

There are limitations to consider. First, and most importantly, the sample size ($n = 38$) was small, and future studies should replicate these findings in larger and more diverse cohorts; bootstrap (10,000 resamples; 95% CI [-0.68, -0.06]) and leave-one-out analyses nonetheless indicated that the key orienting-wSMI-FS-IQ association was stable and not driven by individual observations. Second, the cross-sectional design precludes inferences about developmental trajectories; longitudinal work is required to determine whether reduced orienting-network information sharing predicts later cognitive outcomes. Third, wSMI does not provide information flow directionality. Finally, eye movements were not measured, limiting tests of oculomotor contributions to orienting efficiency.

In conclusion, intelligence in late childhood was associated not with stronger local neural responses, but with reduced distributed nonlinear information sharing within the orienting network. These findings support a developmental account of neural efficiency in which cognitive

ability relates to streamlined, task-relevant network coordination (Hilger et al., 2017b; Langer et al., 2012). Nonlinear connectivity measures such as wSMI may provide sensitive markers of network maturation and individual differences in cognitive development (Imperatorio et al., 2019; King et al., 2013).

4. Methods

4.1. Design considerations and sample size

This cross-sectional study examined within-developmental-stage variation in neurocognitive processes by investigating how distributed EEG connectivity during attentional processing relates to intelligence in 38 children aged 11–14 years. The within-person repeated-measures design (288 experimental trials per participant across four cue conditions and three congruency levels) provides a relatively large number of within-subject observations, allowing stable individual-level estimation of behavioural and electrophysiological indices relative to single-observation designs (Sheridan et al., 2025). Prior EEG studies using comparable information-theoretic connectivity metrics (wSMI) have reported medium-to-large effect sizes relating neural information sharing to cognitive and clinical outcomes with similar sample sizes ($r \approx 0.35$ – 0.50) (Imperatorio et al., 2019; King et al., 2013; Sitt et al., 2014), suggesting that effects in this range are detectable with the present sample. To control for multiple comparisons across electrodes and time points, we employed nonparametric cluster-based permutation testing with 1000 Monte Carlo iterations (Maris and Oostenveld, 2007), thereby reducing the risk of false positives without requiring distributional assumptions. The analytic strategy includes both distributed connectivity (wSMI) and univariate (ERP, theta power) models as parallel predictors of intelligence, providing an internal specificity check that reduces the likelihood that any observed association reflects a general signal artefact rather than a network-level mechanism.

4.2. Participants

Thirty-eight children (20 girls, 18 boys) aged 11–14 years ($M = 12.5$, $SD = 0.7$) took part in the study. Participants were recruited from public schools in the Maule Region of Chile (municipalities of Talca, Linares, Cauquenes, and Molina) through the SEMILLA-UCM educational outreach programme of Universidad Católica del Maule. Enrolment in this programme is restricted to students from public schools serving low-to middle-socioeconomic-status families, which defines the socioeconomic characterization of the sample; individual-level parental education data were not collected. All experimental sessions (EEG and psychometric testing) were conducted at the CINPSI Neurocog laboratory of Universidad Católica del Maule, not in schools.

The study was approved by the Scientific Ethics Committee of Universidad Católica del Maule and conducted in accordance with the Declaration of Helsinki. Written informed consent was obtained from both parents and participants prior to testing.

4.3. Attentional network task (ANT)

Participants completed the Attentional Network Task (ANT) (Fan et al., 2002), which dissociates alerting, orienting, and conflict (executive control) networks (Petersen and Posner, 2012). Testing took place in a dimly lit room, with participants seated approximately 60 cm from the monitor.

Each trial began with a fixation cross, followed by one of four cue conditions (no cue, center cue, double cue, spatial cue). After a 400 ms delay, a target array (congruent, incongruent, or neutral) was presented for up to 1700 ms. Participants indicated the direction of the central arrow as quickly and accurately as possible.

Following a 24-trial practice block, participants completed 288 experimental trials across four blocks of 72 trials each. Cue and target

conditions were counterbalanced across blocks. Three 5-minute rest breaks were provided during the task to minimize fatigue; including practice and breaks, the ANT lasted approximately 45 min, preceded by EEG preparation (cap fitting and electrode-offset verification) of approximately 30 min. The WISC-III was administered in a separate session of approximately 90 min, conducted in the week prior to the EEG recording. A schematic of the paradigm is shown in Fig. 1.

Reaction time (RT) analysis included correct trials with RTs between 200 and 1700 ms. Network scores were computed according to Fan et al (Fan et al., 2002): Alerting = $RT_{NC} - RT_{DC}$; Orienting = $RT_{CC} - RT_{SC}$; Conflict = $RT_{Incongruent} - RT_{Congruent}$.

4.4. Intelligence assessment

Full-Scale IQ (FS-IQ) was assessed using the Chilean standardized version of the Wechsler Intelligence Scale for Children (Ramírez and Rosas, 2007). Raw scores were converted to age-normed scaled scores using Chilean norms. The Chilean standardization reports excellent internal consistency for the Full-Scale IQ (Cronbach's $\alpha = 0.95$; Verbal Scale $\alpha = 0.94$; Performance Scale $\alpha = 0.90$) (Ramírez and Rosas, 2007). FS-IQ ranged from 90 to 134 (mean = 114, $SD = 10.5$). FS-IQ was used in all regression and correlational analyses.

4.5. EEG acquisition

EEG was recorded using a 32-channel BioSemi ActiveTwo system (BioSemi, Amsterdam, The Netherlands) positioned according to the international 10–20 system. Electrooculogram (EOG) electrodes were placed at the outer canthi and above and below the left eye to monitor horizontal and vertical eye movements.

Data were sampled at 2048 Hz (24-bit resolution). BioSemi's common mode sense (CMS) and driven right leg (DRL) electrodes served as reference and ground during acquisition. Electrode offsets were maintained below ± 20 mV. Data were resampled offline to 256 Hz prior to preprocessing.

4.6. EEG preprocessing

Preprocessing was conducted in MATLAB using the FieldTrip toolbox (Oostenveld et al., 2011) and the standardized Automagic pipeline (v2.3.8) (Pedroni et al., 2019) running EEGLAB-based routines, with identical parameters for all participants; the processing of each dataset was archived in an individual log file. The pipeline comprised, in order: (1) offline resampling to 256 Hz; (2) PREP early-stage processing (Bigdely-Shamlo et al., 2015), including temporary 1-Hz high-pass detrending (not applied to the final data), multi-taper line-noise removal at 50 and 100 Hz (CleanLine), robust detection of noisy channels (extreme amplitude $z > 5$, low correlation < 0.4 , RANSAC predictability < 0.75 , high-frequency noise $z > 5$), and robust average re-referencing; (3) zero-phase FIR band-pass filtering (high-pass 0.5 Hz; low-pass 30 Hz; pop_eegfiltnew); (4) removal of ocular activity by regressing out the EOG channels (Parra et al., 2005); (5) ICA decomposition (runica (Delorme and Makeig, 2004)) with fully automatic classification and removal of artifactual components using MARA (Winkler et al., 2011), computed on data temporarily high-pass filtered at 1 Hz (mean 3.6 ± 2.5 components removed per participant, range 0–13); (6) DC-offset removal; (7) spherical-spline interpolation of channels flagged as bad (mean 3.3 ± 1.9 channels per participant, range 0–9); (8) automatic quality assessment of each dataset using the Automagic quality metrics (proportion of high-amplitude samples, OHV; timepoints of high variance, THV; channels of high variance, CHV; ratio of bad channels, RBC), leading to the exclusion of two of the 40 recorded datasets that exceeded the bad-quality cut-offs (OHV or THV > 0.20), yielding the final sample of $n = 38$ (included datasets: OHV $M = 0.006$, $\max = 0.022$; THV $M = 0.049$, $\max = 0.166$); (9) segmentation into epochs from -200 to 2000 ms relative to cue onset (target onset at

500 ms after cue onset); and (10) residual artifact rejection excluding epochs exceeding $\pm 100 \mu\text{V}$. All subsequent analyses were conducted on artifact-free epochs. On average, 277.3 ± 10.2 of 288 trials per participant (96.3%; range 240–288) were retained after preprocessing (no cue: 68.9 ± 3.8 ; central cue: 69.5 ± 2.7 ; double cue: 69.7 ± 2.0 ; spatial cue: 69.2 ± 2.7 ; congruent: 92.2 ± 4.1 ; incongruent: 92.0 ± 4.4 ; neutral: 93.2 ± 2.8 ; [Supplementary Table S1](#)).

4.7. ERP analysis

Cue-locked ERPs were analysed using spatiotemporal cluster-based permutation testing implemented in FieldTrip ([Oostenveld et al., 2011](#)). Each attentional network was indexed by its canonical electrophysiological marker. Cue-locked ERP amplitude modulations were used for alerting and orienting, reflecting cue-evoked preparatory and spatial-selection processes ([Gopalan et al., 2019](#); [Neuhaus et al., 2010](#)), and frontal-midline theta power for conflict processing, the canonical oscillatory signature of executive control ([Cohen and Donner, 2013](#); [Cavanagh and Frank, 2014](#)). This choice provides the best-validated univariate benchmark for each network against which the predictive value of distributed connectivity (wSMI) can be compared.

Dependent-samples *t*-tests were computed across electrodes and time points within a -200 – 2000 ms window relative to stimulus onset. Adjacent samples with $p < 0.05$ were grouped into clusters (minimum two neighboring electrodes within 4 cm). Cluster-level statistics were computed as the sum of *t*-values within each cluster.

Statistical significance was assessed using 1000 Monte Carlo permutations with random label shuffling, following standard procedures for nonparametric cluster correction ([Maris and Oostenveld, 2007](#)). The maximal cluster statistic across permutations formed the null distribution.

4.8. Time–frequency analysis

Time–frequency decomposition was performed using complex Morlet wavelets from 2 to 30 Hz (15 linearly spaced steps). Wavelet cycles increased logarithmically from 3 to 12. Power was computed as the squared magnitude of the complex convolution and converted to decibel change relative to baseline (-400 to -100 ms) ([Cohen and van Gaal, 2014](#)).

A fronto-central region of interest (ROI) was defined a priori for conflict-related theta activity (4–9 Hz) based on prior work ([Cohen and Donner, 2013](#); [Cavanagh and Frank, 2014](#); [Nigbur et al., 2012](#); [Cohen and Ridderinkhof, 2013](#); [Pastötter et al., 2013](#)). Cluster-based permutation testing (incongruent vs. congruent) identified significant time–frequency clusters within -200 – 2000 ms ([Oostenveld et al., 2011](#)). The resulting significant window (825–1675 ms) was used for the conflict-network connectivity analysis (see Weighted Symbolic Mutual Information).

4.9. Weighted symbolic mutual information (wSMI)

Distributed information sharing was quantified using weighted Symbolic Mutual Information (wSMI), an information-theoretic measure sensitive to nonlinear coupling ([Imperator et al., 2019](#); [King et al., 2013](#); [Sitt et al., 2014](#)).

EEG signals were transformed into symbolic sequences defined by the temporal ordering of $\kappa = 3$ samples separated by a temporal lag $\tau = 32$ ms. The frequency sensitivity f is given by:

$$f = \frac{1000}{(\tau \bullet \kappa)}$$

With $\kappa = 3$ and $\tau = 32$ ms, wSMI is sensitive to frequencies below ~ 10 Hz, encompassing the theta band.

For each electrode pair, joint symbol probabilities $p(x, y)$ were computed and weighted to minimize spurious coupling due to common

sources. Identical and opposite symbols were assigned zero weight to reduce trivial correlations ([Imperator et al., 2019](#); [King et al., 2013](#)).

wSMI was calculated as:

$$wSMI = \sum_{x,y} w(x,y) p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$

wSMI was selected because the primary aim was to quantify nonlinear integrative information sharing rather than frequency-specific phase synchronisation. wSMI detects statistical dependencies between symbolic temporal patterns without requiring linearity or stable phase locking, and reduces trivial common-source contributions through its weighting scheme ([Imperator et al., 2019](#); [Vinck et al., 2023](#)). For each participant, wSMI was computed from the condition-specific epochs (not from difference waves) for the conditions defining each ANT network: double-cue vs. no-cue (alerting), spatial-cue vs. central-cue (orienting), and incongruent vs. congruent (conflict). Pairwise wSMI was calculated for all electrode pairs and averaged across pairs to obtain a single global connectivity value per condition and participant; the corresponding condition difference served as the participant-level predictor. Temporal windows were network-specific. In the conflict network, connectivity was computed within the significant theta time window (825–1675 ms) identified in the time–frequency analysis, whereas orienting and alerting wSMI were computed within their respective significant cue-locked ERP windows (360–800 ms and 220–790 ms).

4.10. Statistical analyses of individual differences

Associations between neural measures and FS-IQ were tested with multiple linear regression, conducted separately for the connectivity model (alerting-, orienting-, and conflict-network wSMI) and the univariate model (cue-locked ERP amplitudes and conflict theta power). Coefficients are reported as standardized β with 95% confidence intervals, alongside unstandardized B values. Robustness was assessed with influence diagnostics (Cook's distance and leverage), a nonparametric bootstrap of the orienting-wSMI-FS-IQ correlation (10,000 resamples), and leave-one-out analyses. Following [Der and Deary \(2017\)](#), we further tested whether wSMI explained variance in FS-IQ beyond reaction time using hierarchical regression (Model 1: mean RT; Model 2: mean RT + network wSMI), evaluating the change in explained variance (ΔR^2) with an *F*-change test.

CRedit authorship contribution statement

Boris Lucero: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Renzo C. Lanfranco:** Writing – review & editing, Validation. **Maria Teresa Muñoz-Quezada:** Writing – review & editing, Validation, Methodology, Conceptualization. **Chiara Saracini:** Writing – review & editing. **Andrés Canales-Johnson:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation.

Author contributions statement

B.L. conceived the study; B.L. and A.C.J. developed the methodology; B.L. conducted experimental data collection; A.C.J. and B.L. analysed the data; B.L. R.C.L. and A.C.J., interpreted the findings; B.L., A.C.J., C.S., R.C.L. and M.T. MQ., wrote the manuscript. All the authors revised and edited the manuscript.

Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place. This study was approved by the Scientific Ethics Committee of Universidad Católica del Maule. (Approval No. 79)

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Declaration of Competing interest

The authors declare no competing interests.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.dcn.2026.101821](https://doi.org/10.1016/j.dcn.2026.101821).

Data availability

Data will be made available on request.

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