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Intersubject correlation as a predictor of attention: a systematic review

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Abstract
This meta-analysis examines the challenge of capturing brain activity in real-world and laboratory settings by integrating naturalistic neuroimaging and experimental data with behavioral measures to explore the predictive role of intersubject correlation (ISC) in attention. Using databases such as Web of Science and PubMed, we conducted a comprehensive search from January 2000 to July 2024. Our meta-analysis of 14 studies and 27 effect sizes reveals a significant positive correlation between ISC and attention ($r = 0.65$, $p < 0.001$), demonstrating that ISC serves as a reliable neural marker for attentional engagement under various experimental conditions. By incorporating naturalistic stimuli such as video clips and controlled laboratory tasks, we provide insights into the application of ISC to predict attention in ecologically-valid contexts. Moreover, our addition of behavioral data further enhances the understanding of how neural synchronization reflects attentional states. Our results underscore the potential of utilizing ISC to develop personalized assessments and interventions in educational and cognitive settings.

Keywords Intersubject correlation (ISC), Attention, Neural synchronization, Naturalistic neuroimaging, Meta-analysis, Cognitive neuroscience

Introduction

Intersubject correlation (ISC), an emerging metric in cognitive neuroscience, reflects the similarity of neural responses among multiple individuals engaged in the same task [1]. This synchronization is regarded as an indicator of attentional focus and cognitive engagement [2]. Although ISC has been extensively applied, the understanding of its validity and underlying mechanisms as a predictive marker for attention remains incomplete, providing fertile ground for further investigation. ISC can serve as a proxy for learning outcomes in the educational context [3] and can indicate the degree of audience engagement with presented information in the mass media setting [4]. Meanwhile, ISC can offer a new perspective for understanding attentional and emotional processing during musical experiences [5]. These specific applications emphasize how ISC can reflect the degree of attentional focus and reveal the extent of emotional engagement [6]. In this context, stronger coupling between individuals suggests a deeper level of involvement. In this review, attentional engagement refers to the allocation of cognitive resources to externally presented stimuli, such as sustained focus and task-directed processing [7, 8]. While some studies used related proxies (e.g., learning performance or arousal), we only included those aligned with attention-related cognitive engagement.

Hyperscanning enables researchers to simultaneously record neural activity in multiple individuals, facilitating the exploration of ISC during social interactions,

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collaborative tasks, and shared stimuli. This approach allows for a more nuanced understanding of ISC as it emerges in various contexts; particularly in the educational setting and in team-based collaborations, where hyperscanning has demonstrated significant value. Specifically, electroencephalographic (EEG) hyperscanning has been widely recognized for its ability to capture fine-grained temporal dynamics during joint actions, thereby providing critical insights into the neural processes underlying social coordination. These insights underscore the importance of hyperscanning as a robust tool for investigating how ISC unfolds among multiple individuals [9, 10]. For example, hyperscanning has been used to investigate brain activity between teachers and students, providing insights into the neural foundations of effective teaching practices [11]. In studies on team-based collaborations [12], hyperscanning has proven useful for evaluating the efficacy and efficiency of teamwork. In this review, ISC is defined as the similarity of neural responses across individuals exposed to the same time-locked stimuli. It is typically computed using Pearson correlation of time-series data across participants, derived from EEG (e.g., coherence, phase-locking value, or spectral power correlation) or fMRI (e.g., voxel-wise or ROI-level BOLD signal correlation) [13].

Advancements in neuroimaging technology, particularly in ISC measurement techniques such as Pearson correlation and spectral coherence, and the use of hyperscanning, have seen widespread application. Spectral coherence, in particular, allows researchers to quantify ISC within specific neural frequency bands (e.g., alpha, theta), which is especially useful for investigating the oscillatory dynamics of attention [14, 15].

The research has further demonstrated that ISC is a reliable indicator of effective cognitive processing, as observed in contexts in which there is a strong coupling of neural signals in the brain [16]. Changes in attention corregulate ISC across different physiological signals, and the strength of these signals can predict participants' effective memory retention. This suggests that ISC is a physiological phenomenon that reflects the cognitive processing of shared stimuli. Therefore, understanding the role of ISC in the distribution of attention and the processing of salient information is of critical importance. Substantial evidence has supported the role of ISC—an inter-subject neural similarity measure—in reflecting individual attentional states. Although ISC is computed across participants exposed to the same stimulus, it is increasingly recognized as a reliable neural marker that represents an individual's level of attentional engagement during shared experiences [17]. The dorsolateral prefrontal cortex (dlPFC) plays a crucial role in attention control [18], whereas the parietal cortex is involved in the processing of information flow during attention.

However, though the research has explored the link between ISC and attention, the specific mechanisms through which attention levels influence ISC under different natural stimuli, such as narratives and educational videos, require further investigation. Further, the effects of various attention manipulations (e.g., intentional vs. incidental learning) and how changes in ISC within different frequency bands (e.g., alpha and theta waves) reveal the neural mechanisms of attention have not been thoroughly studied, including EEG, functional magnetic resonance imaging (fMRI) data, and eye tracking and behavioral measures, to explore how attention modulates ISC and its role in cognitive processing. Therefore, we conduct a meta-analysis to better understand the relationship between neural mechanisms and ISC. We aim to provide new insights into the complex relationship between attention and ISC, with potential application in the educational and clinical settings.

Methods

Inclusion criteria

This meta-analysis adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [19] and focused on factors related to attention. Attention is a crucial component of cognitive function that significantly affects learning, work efficiency, and daily activities. Therefore, understanding the factors that influence attention has important theoretical and practical implications. The inclusion criteria for this meta-analysis were studies that were: (1) published between January 2000 and July 2024, (2) written in English, (3) experimental in nature, and (4) involved tasks related to attention. The exclusion criteria were as follows: (1) non-English publications, to ensure accessibility and quality; (2) Non-experimental studies were excluded; (3) studies that did not involve attention-related tasks, so as to maintain relevance to the attention research; (4) involved clinical populations (e.g.,ADHD); (5) examined intra-individual rather than inter-subject synchrony; (6) did not report extractable effect sizes.

We obtained 18 studies that examined the relationship between ISC and attention. We excluded four studies from the final analysis: three that did not report specific effect sizes and one that provided a range of correlation coefficients between ISC and attention. Consequently, our meta-analysis included 14 studies, with 27 effect sizes and 619 participants. Our objective was to explore the variability of effect sizes across different studies and within individual studies, and identify the potential factors influencing the ISC–attention relationship. We used a three-level meta-analysis method for a detailed examination of this relationship across various experimental conditions, study designs, and sample sizes. The publication date range (January 2000 to July 2024) was selected because hyperscanning techniques—especially those involving fMRI—only began to emerge after 2000, with one of the earliest studies conducted by Montague et al. [20].

Search strategy

We searched for relevant literature PubMed, Scopus, EBSCO, ScienceDirect, and Web of Science using the following search queries: (ISC OR intersubject correlation OR intersubject consistency OR neural alignment OR interbrain coupling) AND (attention OR attentional OR engagement).

Selection process and data extraction

We initially identified 2,465 articles through database searches. After removing 515 duplicates, 1,950 records remained for screening. Of these, 1,926 were excluded based on title and abstract. The remaining 22 full-text articles were assessed for eligibility. Four studies were excluded at this stage: two studies focused on populations with clinical conditions (e.g., ADHD), and two investigated intra-individual (rather than inter-subject) brain correlations. This resulted in 18 eligible studies. However, four of these did not report extractable effect sizes and were excluded from the final meta-analysis.

Although our review focuses on ISC as a neural marker of attention, we included studies that used ISC metrics such as coherence or phase-locking if the analysis approach was methodologically comparable to ISC (i.e., computing inter-individual synchrony in response to shared stimuli).

Consequently, our meta-analysis included 14 studies, with 27 effect sizes and 619 participants. Figure 1 shows a flowchart of the screening process, highlighting the inclusion and exclusion steps. Table 1 provides the characteristics and methodological aspects of the included studies, including the sample size, study type, control variables, measurement tools, experimental materials, and task types.

Data handling and analysis

In this review, we defined ISC as the similarity of neural responses across individuals exposed to the same time-locked stimuli. ISC values were derived from different modalities: electroencephalography (EEG) studies commonly used temporal synchronization metrics such as coherence, phase-locking value (PLV), or correlation of spectral power across subjects [21, 22], while functional magnetic resonance imaging (fMRI) studies calculated voxel-wise or region-based correlations of blood-oxygen-level-dependent (BOLD) signal time courses between participants [13, 23]. We considered these metrics comparable as long as they captured inter-individual synchrony in response to common stimuli.

We extracted or calculated the correlation coefficients of ISC and attention from each included study. As these coefficients did not follow a normal distribution, we transformed them into Fisher's z-scores [24, 25] to compute the main and moderation effects. After calculation, we reconverted the Fisher's z-scores back to the correlation coefficients for interpretation.

Traditional meta-analysis methods assume that effect sizes are independent, leading to the extraction of only one effect size per study [26]. However, many of our included studies reported multiple effect sizes. Multiple effect sizes within the same study are often correlated because they are derived from the same sample. Traditional methods overlook this correlation, potentially leading to overestimation of the overall effect size [27]. Conversely, the three-level meta-analysis approach addresses the dependence among effect sizes within the same study, thereby maximizing information retention and increasing statistical power [28].

Therefore, we employed a three-level random effects model to test the main effects, assess the heterogeneity, evaluate the moderation effects, test for publication bias, and conduct sensitivity analyses. Specifically, in our three-level model, Level 1 represents the sampling variance of each effect size, Level 2 reflects the variance among multiple effect sizes within the same study, and Level 3 captures the variance across studies. The model was implemented in R (version 4.3.3) using the meta for package [29], and variance components were estimated using the restricted maximum likelihood (REML) method.

Due to the limited number of studies in each moderator category, we did not conduct formal meta-regression. Instead, we qualitatively compared effect size patterns across categories of task type (e.g., narrative, music, learning), measurement modality (e.g., EEG, fMRI, eye-tracking), and attentional outcome type (e.g., engagement, learning outcomes) to explore potential sources of heterogeneity. All moderators were treated as categorical variables.Interaction effects were not examined due to the small sample size in each subgroup [30, 31].

Results

Overview of included studies

Before presenting the effect size analysis, we summarize the characteristics of the included experimental studies in Table 1 to provide context for interpreting the reported ISC–attention relationships. ISC refers to the similarity of neural responses across individuals exposed to the same time-locked stimuli, operationalized through EEG (e.g., coherence, phase-locking value, or spectral power correlation) or fMRI (e.g., voxel-wise BOLD signal correlation). Attentional engagement was assessed using indicators such as self-reported ratings, task performance,

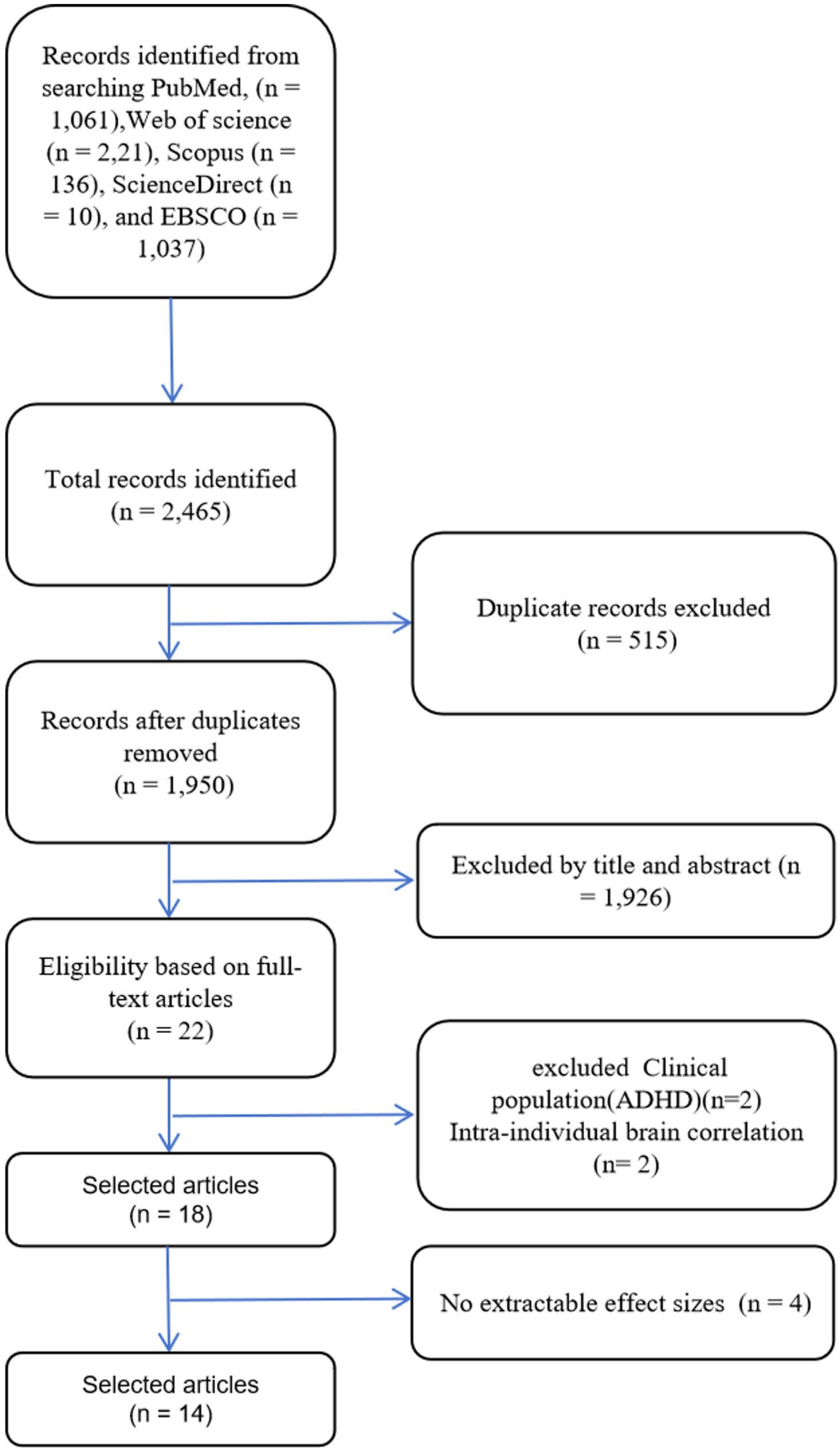

Fig. 1 The flowchart of the screening process

Table 1 Detailed study descriptions and methodologies

ID	Study	Country	Study Type (sample size)	Control Variables	Measurement Tools	Experimental Materials	Task Type
1	Smirnov & Saarimäki (2019)	Finland	Experimental study (2 narrators and 16 listeners)	Age, language proficiency	fMRI	35 stories (pleasant, neutral, unpleasant)	Narration and listening to stories
2	Kaneshiro et al. (2024)	USA	Experimental study (23)	Musical training (≥ 5 years)	EEG, CB	Cello concerto	Listening to music
3	Schmälzle & Grall (2020)	Germany	Experimental study (22)	Suspense plot	fMRI	Watching Alfred Hitchcock movie clips containing suspenseful scenes	Watching movie clips
4	Dauer et al. (2021)	USA	Experimental study (30)	NA	EEG	Listening to Steve Reich's Piano Phase	Listening to music
5	Kaneshiro et al. (2024)	USA	Experimental study (23)	Participants' musical backgrounds	EEG, CB	Musical pieces	Listening to music
6	Abrams et al. (2013)	USA, Canada	Experimental study (17)	Age, gender, handedness	fMRI	Symphonic music excerpts	Listening to natural music
7	Su et al. (2024)	China	Experimental study (29)	Learning styles, Prior knowledge	Eye Tracking	Watching lecture videos from "Digital Photography Fundamentals" on MOOC	Video-learning task
8	Ohad & Yeshurun (2023)	Israel	Experimental study (25)	Age, sex, handedness	fMRI	Listening to a one-hour narrative	Listening to a narrative
9	Poulsen et al. (2017)	Denmark, USA	Experimental study (33)	Age, viewing condition	EEG	Watching video clips from "Bang! You're Dead" and "Sophie's Choice"	Watching video clips
10	Cohen et al. (2018)	USA	Experimental study (36)	Age, prior knowledge, video type	EEG	Watching online educational videos	Watching videos
11	Stuldreher (2020)	Netherlands	Experimental study (26)	Age, sex, task condition	EEG, EDA, heart rate	Listening to audio stimuli, affective sounds, and beeps	Listening to audio stimuli
12	Stuldreher et al. (2020)	Netherlands	Experimental study (27)	Group type (AA or SA), stimulus type (emotional or beeps)	EEG, EDA, heart rate	Watching informative videos	Listening to stories
13	Liu et al. (2023)	China	Experimental study (50; 24 for experiment 1), 26 for Experiment2)	Video type, presence of eye-tracking movements, modeling examples	Eye tracking (EyeLink 1000)	Watching videos on immunology, astrophysics, AI, innovative thinking	Watching videos
14	Madsen & Parra (2022)	USA	Experimental study (92)	Attention (through distraction task)	EEG, eye tracking	Watching informative videos	Watching videos

Note: AI = artificial intelligence, ISC = intersubject correlation, INS = interpersonal neural synchrony, EEG = electroencephalography, CB = continuous behavioral, fMRI = functional magnetic resonance imaging, EDA = electrodermal activity, AA = affective arousal, SA = socially arousing, UK = United Kingdom, USA = United States of America, MOOC = massive online open courses

eye-tracking data, or physiological synchrony (e.g., heart rate), reflecting cognitive resource allocation to shared stimuli.

Table 1 summarizes the backgrounds and key characteristics of the 14 studies included in the analysis, published between 2013 and 2024. Among them, 10 were conducted in the United States of America (USA) [3, 5, 32–39], two were conducted in China [40, 41], one was conducted in Israel [42], two were conducted in the Netherlands [43, 44], one was conducted in Germany [45], and one was conducted in Italy [46].

The studies employed various interactive tasks, such as video learning and lectures, to simultaneously collect EEG data from students and instructors. Fifteen studies were conducted in controlled laboratory settings; these focused on the use of ISC to evaluate its relationship with engagement and attention. Of these studies, 13 employed EEG to measure ISC through spectral coherence and other synchrony metrics [6, 32, 45], whereas four studies used fMRI to analyze brain activity patterns [37, 42, 47, 48]. Spectral coherence values ranged from zero (no synchrony) to one (full synchrony), representing a quantifiable metric of ISC.

Some studies incorporated eye-tracking technology to assess attention using gaze patterns and eye movements [40, 41]. These studies combined EEG and fMRI data to enhance the understanding of attention and engagement prediction through multimodal physiological and behavioral measurements.

Meanwhile, some studies solely utilized eye-tracking or behavioral data without integrating neuroimaging tools. For example, two studies analyzed the consistency of participants' eye movement trajectories while watching videos or performing learning tasks, and revealed that participants with higher attention levels exhibited greater consistency in their eye-movement trajectories [40, 41]. This suggests that ISC can serve as an effective objective indicator for assessing the degree of attentional engagement. Some studies used eye-tracking measures such as gaze patterns and fixations to assess attention, and combined them with neural data (EEG or fMRI) to enhance predictions of attentional engagement. These multimodal designs allowed researchers to evaluate ISC alongside behavioral indicators of attention during shared learning or viewing experiences. Figure 2 presents a forest plot based on the reported effect sizes across included studies. These effect sizes, drawn directly from the original studies and reported in Table 2, show considerable variability. For example, reported Cohen's *d* values range from 0.22 to 34.70, highlighting the heterogeneity in study findings. A formal analysis using a three-level meta-analytic model is presented in Sect. 3.2.

Meta-analytic model of ISC and attention

To further explore the relationship between ISC and attention, we next employed a three-level meta-analytic model.The overall pooled effect size (represented by the diamond at the bottom) is 0.78 [95% CI: 0.5, 1.05], indicating a strong positive relationship between ISC and attention. The results indicated a significant positive correlation between ISC and attention ($r = 0.65$, degree of freedom [df] = 26, $p < 0.001$), with a 95% confidence interval (CI) [0.46, 0.78]. Although some publication bias was detected, the overall effect remained positive. Potential reasons for this bias could be due to the omission of effect sizes in some studies, or the significant differences in the measurement tools used. According to Cohen's criteria [49], this correlation coefficient represents a large effect size, suggesting a strong association between ISC and its ability to positively predict attention. All effect sizes were extracted and coded by a single researcher using a standardized protocol. As only one rater was involved, inter-rater reliability was not applicable.

In the variance component analysis, the within-study variance (level 2, σ^2 = 0.0358, $p < 0.001$) and between-study variance (level 3, σ^2 = 0.2254, $p < 0.001$) exhibited significant differences. Within-study variance reflected the variance among different effect sizes within the same study, while between-study variance captured the variance in effect sizes across different studies. Although the exact proportion of sampling variance (level 1) was not provided, the significant contributions of the within-study and between-study variance highlighted the need for us to further examine the potential moderators to better elucidate the relationship between ISC and attention.

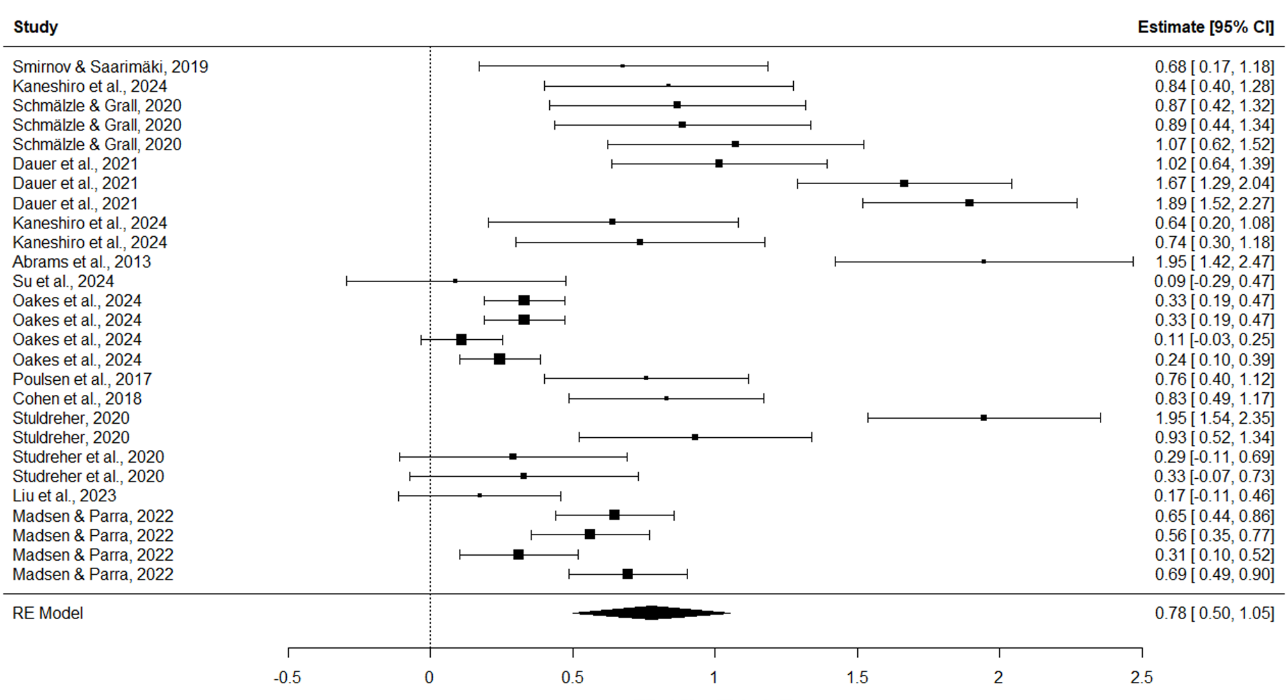

Fig. 2 The forest plot

Table 2 Summary of included studies on ISC and attention

ID	Study	Independent variable	Dependent variable	Method of measuring attention	Relationship between attention and ISC
1	Smirnov & Saarimäki (2019)	Emotional dialogue (pleasant, neutral, unpleasant)	Neural alignment	Self-reported emotional arousal	Emotional arousal ($r = 0.59$, $p < 0.001$)
2	Kaneshiro et al. (2024)	Engagement	INS, engagement	Self-reported engagement using a slider	The remixed (phase-scrambled) version had the highest EEG and ISC values, showing the strongest INS ($p < 0.001$, d = 5.1). The lowest values were under the tremolo condition ($p = 0.41$, d = 0.7).
3	Schmälzle & Grall (2020)	Degree of suspense in the plot	Neural synchronization of suspense regions (mid-cingulate gyrus, angular gyrus, lateral prefrontal cortex)	Suspense ratings (continuous)	mid-cingulate gyrus: $r = 0.70$; angular gyrus: $r = 0.71$; lateral-prefrontal cortex: $r = 0.79$
4	Dauer et al. (2021)	Repetitiveness and rhythmic variations of music	EEG and ISC, CB and ISC, overall and time-resolved engagement	Emotionally-arousing moments reflect attentional engagement	ISC of EEG (original: $d = 2.4$, remixed: $d = 5.1$), ISC of CB (original: $d = 6.5$, remixed: $d = 34.7$)
5	Kaneshiro et al. (2024)	Music stimulus type	ISC and behavioral ratings	EEG and ISC, ISC and CB responses	ISC of EEG: $z = 3.57$, $p < 0.001$; ISC of CB: $z = 4.19$, $p < 0.001$
6	Abrams et al. (2013)	Type of musical stimulus (natural music, spectrally-rotated, phase-scrambled)	Intersubject synchronization among various brain regions	Emotionally-arousing moments reflect attentional engagement	Z-value for left Heschl's Gyrus is 12.831.
7	Su et al. (2024)	ISC of eye movements	Self-reported attention levels, learning outcomes	Self-reported attention levels (1–9 scale)	ISC of eye movements: attention vs. distraction ($t(28) = 17.36$, $p < 0.001$; $d = 3.22$ $r = 0.09$, $p = 0.65$)
8	Oakes et al. (2024)	Audience facial expression synchrony	Audience engagement predictions	Facial expression analysis	Correlation between ISC of facial expression and engagement: Neutral: $r = 0.59$, happy: $r = 0.60$, anger: $r = 0.5$, disgust: $r = 0.39$
9	Poulsen et al. (2017)	ISC	Neural engagement and attention	ISC during video presentation	ISC of "Bang! You're Dead": $r = 0.64$, $p < 0.01$; ISC of "Sophie's Choice": $r = 0.46$, $p = 0.014$
10	Cohen et al. (2018)	Engagement with the narrative	INS, comprehension performance	EEG-based (ISC)	ISC: $r = 0.68$, $p < 0.001$
11	Stuldreher (2020)	Physiological synchrony among EEG, EDA, heart rate	Classification accuracy of attentional state	EEG, EDA, heart rate data synchronization	EEG synchrony classification accuracy: 96% EDA synchrony classification accuracy: 73%
12	Stuldreher et al. (2020)	Attentionally-engaging events	Physiological synchrony among EEG, EDA, heart Rate	Continuous self-reported engagement ratings	EEG: AUC = 0.642 ($p < 0.001$) for beep detection EDA: AUC = 0.658 ($p < 0.001$) for emotional sound detection
13	Liu et al. (2023)	Attentional engagement	ISC values, test scores	Continuous eye tracking, questionnaires	$r = 0.172$
14	Madsen & Parra (2022)	Attentional engagement	ISC, memory performance	Fully-attentive condition and distracted condition	ISC of EEG: $r = 0.57$ ($p < 0.001$) ISC of pupil size: $r = 0.51$ ($p < 0.001$) ISC of heart rate: $r = 0.30$ ($p = 0.05$) ISC of gaze position: $r = 0.60$ ($p < 0.001$)

Note: ISC = intersubject correlation, EEG = electroencephalography, CB = continuous behavioral, INS = interpersonal neural synchrony, fMRI = functional magnetic resonance imaging, DMN = default mode network, VAN = ventral attention network, CN = central network, AUC = area under the curve. DAN: Dorsal Attention Network, SM: Sensorimotor Network, EDA: Electrodermal Activity

The heterogeneity test results ($Q_{(df = 26)} = 271.43$, $p < 0.001$) revealed significant heterogeneity among the studies. Therefore, we explored the potential factors influencing the relationship between ISC and attention among the included studies.

Publication bias test

We next conducted Egger's test based on the Fisher's z-scores to test for potential publication bias. First, we used the restricted maximum likelihood estimation to analyze the 27 effect sizes. The variance components showed that the between-study variance (sigma^2.1 = 0.2070) and within-study variance (sigma^2.2 = 0.2239) exceeded zero, indicating variability in the effect sizes within the same studies and across different studies.

The Egger's test results revealed that the intercept estimate was −0.0769 (standard error [SE] = 0.5652, z =

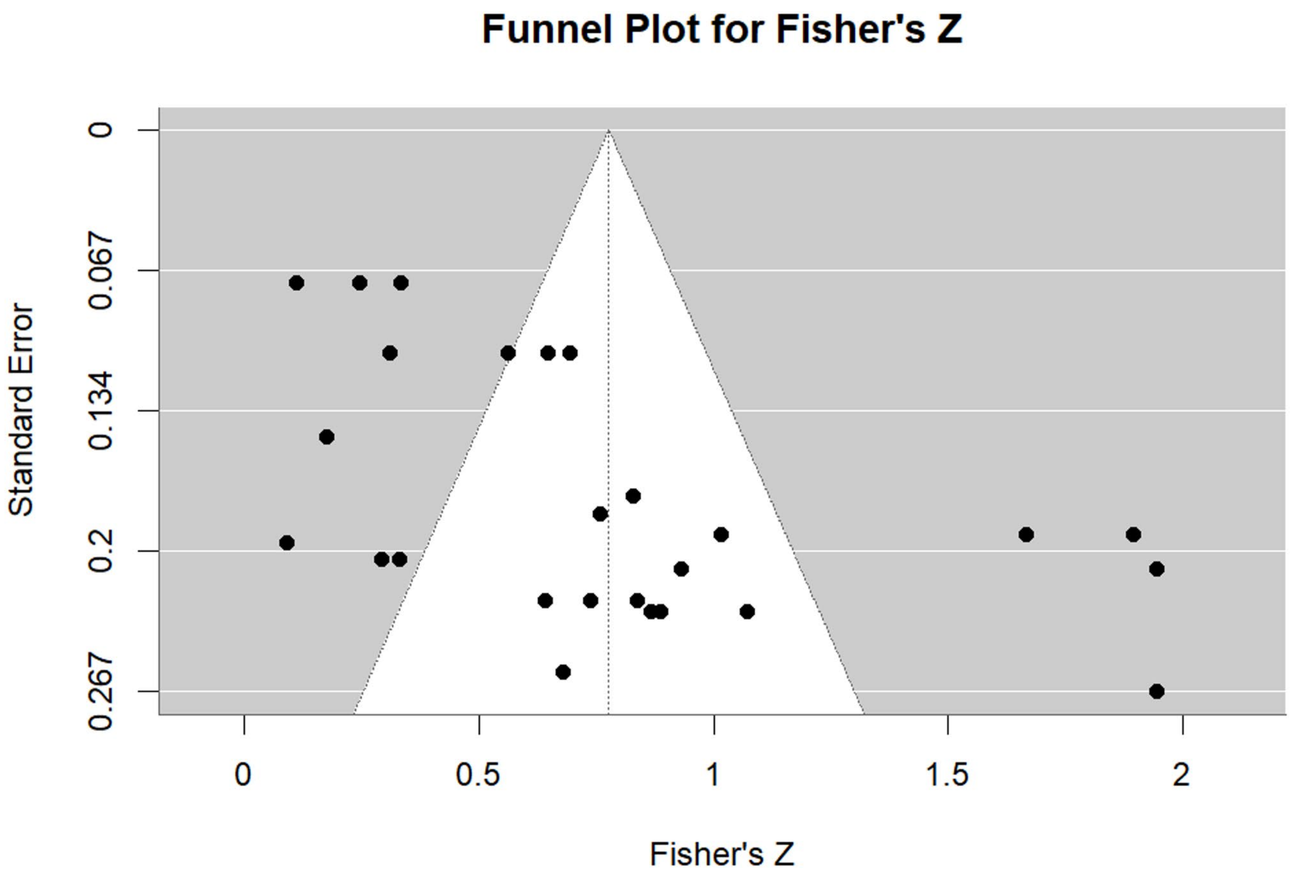

Fig. 3 Funnel plot for Fisher's Z

-0.1361, $p = 0.8917$), indicating that the average effect size estimate was not statistically significant. The 95% CI was [-1.1846, 1.0307]. As shown in Fig. 3, the funnel plot for Fisher's Z values does not exhibit a perfectly symmetrical distribution, suggesting the presence of potential publication bias. However, the relationship between the SE of the effect size and the effect size magnitude was marginally significant (estimate = 4.9322, SE = 2.9308, $z = 1.6829$, $p = 0.0924$), suggesting some publication bias. In sum, although residual heterogeneity was significant, the Egger's results suggested that publication bias was not a major concern because the effect of the SE on the effect size estimate was only marginally significant.

ISC as a predictor of attention: measurement tools in Meta-Analysis

The selected studies (Table 2) widely used EEG to measure participants' ISC when engaged in the same task [35]. Due to its high temporal resolution, EEG enables researchers to capture the timing of neural signals during specific tasks and compare them among participants, offering unique advantages when studying dynamic cognitive processes such as attention and emotional responses [50, 51]. For example, Dauer et al. [33] used EEG to investigate ISC while participants listened to minimalist music, such as Steve Reich's "Piano Phase," exploring how musical repetition and rhythmic variation influence neural engagement. By analyzing ISC among participants, researchers can investigate how synchronized activities reflect participants' emotional engagement with and understanding of music to evaluate the degree of ISC when processing the same stimulus [32].

Despite the excellent temporal resolution of EEG, its relatively low spatial resolution limits the precise localization of specific brain regions. This limitation can be partially addressed when combined with fMRI, which measures blood-oxygen level-dependent signals. This has enabled the precise localization of brain regions associated with cognitive activities, and complements EEG [52]. By integrating EEG and fMRI, researchers have obtained multifaceted evidence when studying ISC [53], as EEG provides the temporal dynamics of neural activity, while fMRI pinpoints the specific brain regions involved. This integration allows for a more comprehensive understanding of the neural mechanisms underlying complex tasks from different perspectives.

ISC is regarded as a crucial indicator of attention, cognitive engagement, and social interaction. The included studies showed that higher ISC is often associated with stronger emotional responses, enhanced comprehension, and deeper cognitive and emotional resonance. For example, in natural music-listening tasks, ISC can effectively capture variations in participants' emotional and cognitive engagement [32]. Similarly, in other tasks, such as narrative engagement or collaborative learning, ISC has been closely linked to participants' attention and cognitive states [54].

In video-based learning tasks, ISC can reflect participants' focus on learning content and reveal the effectiveness of collaborative learning among groups [55]. These tasks are designed to elicit participants' attention and cognitive engagement, thereby allowing researchers to evaluate cognitive and emotional processing in complex naturalistic scenarios by measuring ISC [56]. The advantage of this approach lies in its ability to provide insights into individual neural activity while revealing the mechanisms of brain collaboration in group interactions or joint tasks, thus offering new perspectives on collective attention and learning processes.

Some studies have combined hyperscanning techniques with physiological indicators to capture emotional synchrony and autonomic coupling during cooperative tasks. For example, by recording participants' galvanic skin response (GSR) and heart rate (HR) during tasks, the research [57] has revealed dynamic changes in emotional and physiological responses during cooperation. When participants received positive feedback during cooperation, the synchrony of their GSR and HR significantly increased, indicating enhanced emotional resonance and social bonding. Additionally, changes in task difficulty and execution modes can affect interbrain synchrony, with more significant brain coordination observed under complex tasks or highly cooperative conditions [58]. Therefore, by integrating multimodal data, researchers can gain a more comprehensive understanding of the dynamic changes in emotional, attentional, and physiological responses under different task conditions.

Relationship between interbrain coupling and attention

ISC and engagement

The research has indicated that ISC exhibited significant variability across different task types: complex or emotionally-engaging stimuli tend to elicit higher ISC values, suggesting that participants allocate more cognitive resources to these tasks [59]. For example, Dauer et al. [33] and Schmälzle and Grall [45] found that in tasks involving music and videos, participants often demonstrate stronger ISC, indicating the closer alignment of their brain activity when perceiving and processing complex information. Kaneshiro et al.'s [5] EEG recordings reveal that the participants' brain activity is highly synchronized within specific frequency bands when listening to music, particularly during complex segments, reflecting deeper cognitive processing and emotional resonance. This finding supports the effectiveness of ISC as a measure of engagement. Taken together, these findings suggest that ISC is a reliable neural marker of attentional engagement across various naturalistic and semi-controlled paradigms. Whether participants were listening to narratives, watching educational videos, or engaged in classroom learning, higher ISC consistently corresponded to greater behavioral or subjective engagement.

Moreover, studies that manipulated attentional focus—by introducing distractions or contrasting focused versus unfocused conditions—demonstrated that ISC is sensitive to attentional fluctuations, further supporting its utility in capturing engagement dynamically.

Influence of task types

Task type significantly affects ISC. Some of the included studies found that higher task complexity and emotional involvement were associated with higher ISC scores [36, 46]. Different modalities, such as narrative and music listening tasks, have consistently demonstrated significant ISC effects [5, 36]. Listening to natural music has been shown to elicit significant ISC, particularly at frequencies related to rhythm and beat, reflecting its role in engaging complex emotional and cognitive processes [32].

Additionally, suspenseful scene-watching tasks [34] produces high levels of ISC, particularly in regions such as the mid-cingulate cortex, angular gyrus, and lateral prefrontal cortex. These regions are implicated in salience detection, attentional allocation, and executive control, which may explain their involvement in processing emotionally arousing and attention-grabbing content [60, 61]. Similarly, the free-viewing of emotional movie clips [46] results in high ISC values, suggesting that watching emotional content in movie clips produces significant ISC within the delta, alpha, and gamma bands.

Key brain regions and ISC

Significant ISC has been observed in the prefrontal cortex and temporoparietal junction during task performance, with Adebimpe et al. [62] identifying these regions as critical for attention allocation and cognitive control.For example, in the prefrontal cortex is particularly prominent when participants engage in complex cognitive tasks [37], indicating that the prefrontal cortex plays a key role in supporting high-level cognitive activity. The research has also shown that during the processing of socially-relevant and conflict-filled movie scenes, brain regions such as the posterior superior temporal sulcus, middle temporal gyrus, and medial prefrontal cortex exhibit significant ISC, reflecting heightened engagement and processing of social stimuli [63]; this finding supports the role of these regions in complex cognitive processing. Brain areas associated with emotional processing, such as the amygdala and hippocampus, also display higher ISC values during emotionally-driven tasks. For example, Maffei [46] reveals that when viewing emotional movie clips, ISC within different frequency bands (e.g., delta, alpha, and gamma) significantly increase. This finding suggests that these brain regions play important roles in regulating the relationship between emotion and attention.

ISC as a predictive measure of attention

Table 2 further summarizes the relationship between attention measurement methods and interbrain coupling across the included studies, and demonstrates the predictive power of ISC on attention under various conditions. As a manifestation of ISC, ISC has been widely studied and applied when assessing attention. The research has shown that ISC can effectively predict participants' attention levels across different task contexts and is closely related to the allocation of cognitive resource [15]. For example, Su et al. [41], use eye-tracking technology to measure participants' ISC during an online video learning task; they reveal that higher ISC values are significantly correlated with participants' self-reported attention levels ($t_{(28)} = 17.36$, $p < 0.001$, $d = 3.22$). Meanwhile, Liu et al. [40] find a positive correlation between ISC values and learning outcomes ($r = 0.172$), indicating that ISC reflects immediate attentional states and can predict long-term learning outcomes.

Moderating effect of experimental conditions on ISC

When investigating ISC as a predictor of attention, Madsen and Parra [64] found that experimental conditions significantly modulated ISC performance, with significant differences in ISC between fully-focused and distracted states. Under the fully-focused experimental condition, participants showed significantly higher ISC values ($r = 0.57$, $p < 0.001$), whereas ISC values decreased in the distracted condition. Dauer et al. [33] reported that different types of task materials and stimuli significantly impacted ISC. Specifically, the repetitiveness and rhythmic variation of music affected participants' ISC: complex rhythms enhanced ISC, while repetitive stimuli led to reduced ISC.

Under the fully-focused experimental condition, participants show significantly higher ISC values ($r = 0.57$, $p < 0.001$), whereas ISC values decrease in the distracted condition.Dauer et al. [33] reveal that different types of task materials and stimuli significantly impact ISC. Specifically, the repetitiveness and rhythmic variation of music affect participants' ISC: complex remixed versions elicit higher ISC values ($d = 5.1$), while the simpler music elicits lower ISC values ($d = 2.4$). This finding is consistent with neural entrainment theories suggesting that cortical oscillations synchronize with the temporal regularities of external stimuli, especially in the context of rhythmically complex auditory input. Studies have shown that complex, structured rhythms can enhance neural entrainment, which in turn supports stronger intersubject synchronization [65, 66]. Moreover, as Lakatos et al. highlight, entrainment to auditory stimuli facilitates attention by aligning internal neural excitability with external events [67]. These mechanisms may underlie the observed ISC differences across musical complexity levels, reinforcing the notion that ISC is sensitive to the temporal dynamics and attentional demands of stimuli.

Application of ISC in different fields

Due to the advancements in neuroscience, the application of ISC as a predictive measure of attention has expanded beyond the traditional educational and psychological research fields, and has shown great potential in advertising, marketing, and human–computer interactions. For example, in the advertising field, Oakes et al. [39] use ISC to predict the relationship between audience engagement and advertisement effectiveness by analyzing viewers' facial synchrony when watching different types of emotional content. Specifically, they show that viewers' facial synchrony was positively correlated with emotional arousal, with moderate to strong correlations found for both neutral ($r = 0.59$) and happy ($r = 0.60$) emotional conditions. These results suggest that ISC-related metrics may serve as effective indicators of audience engagement, offering practical value for evaluating advertisement effectiveness.

Discussion

The ISC and attention domains were previously considered relatively independent, with little connection between them. However, increasing evidence has suggested a significant link between them, particularly in activities that demand high levels of engagement or involvement [33]. These activities are often accompanied by notable changes in the nervous system, which provides a new perspective for understanding the underlying mechanisms of attention. The research has predominantly focused on how individuals' neural activity reflects attention but has overlooked how ISC during interpersonal interactions influences or predicts individuals' attention levels [68]. With technological advancements such as hyperscanning, we can better observe and understand how ISC during interpersonal interactions reflects participants' attentional states and performance in complex task situations [69]. This interdisciplinary integration expands the understanding of attention and provides a more complex and dynamic framework for capturing changes in attention within social contexts [70]. Accordingly, our meta-analysis examines 14 studies on changes in ISC to uncover its potential connection with attentional processes. Our results suggest new research directions for and potential applications of ISC as a tool for use in educational and team collaboration settings that require high levels of interaction.

Increased ISC and attention research, and the analytical challenges

Due to the rapid development of neuroscience technology, particularly the widespread application of hyperscanning, the ISC research has made significant progress in exploring the relationship between attention and social interactions [13]. Hyperscanning enables researchers to simultaneously record the brain activity of multiple individuals engaged in a common task or interaction, so as to provide a new methodological tool for examining the relationship between ISC and attention. Traditional attention research often focuses on the division between external and internal processes at the individual level [71]; however, the increase in the ISC research suggests that attention may not be solely an internal phenomenon but may be influenced by other individuals during social interactions.

Nevertheless, the cognitive significance of ISC in attention regulation remains controversial. Some studies have suggested that ISC may reflect ISC among individuals engaged in a common task [72]. However, the specific mechanisms underlying this phenomenon are not yet fully understood. Moreover, ambiguity remains in the definition of ISC, which may lead to confusion with other neural synchrony phenomena, such as attention-enhanced neural synchrony. Therefore, the future research should define ISC more clearly and control for the influence of attention factors when designing experiments.

Another challenge pertains to the diversity of analytical methods. The ISC research has employed various methods, including spectral analysis, phase synchrony analysis, and cross-correlation analysis. Which these methods have provided rich perspectives, they have also led to issues regarding the comparability and reliability of the results [73, 74]. Therefore, to improve the comparability and reliability of the results across studies, researchers have called for the adoption of more standardized analytical methods in the ISC research [75].

Prospects and challenges in ISC application

Potential use of ISC as an assessment tool

The characteristics of ISC make it a powerful tool for evaluating attention and engagement in educational and social environments. In the educational setting, ISC can be used to monitor students' real-time attention and engagement levels, which can help educators to adjust their teaching strategies and provide personalized learning support. For example, in massive open online courses (MOOCs), ISC can help to identify decline in students' attention and improve learning outcomes by adjusting course content or increasing interactivity [41]. Additionally, in interactive learning scenarios, ISC can evaluate the effectiveness of collaboration between educators and students, which can help educators to improve their teaching methods and enhance students' learning experience [76].

In the advertising and marketing setting, ISC can assess audiences' emotional resonance and engagement. By monitoring viewers' ISC when watching advertisements, researchers can evaluate the appeal of advertisements and the effectiveness of information delivery, whereas can help designers to optimize content and choose the optimum communication strategies [77]. Further, ISC can evaluate the cross-cultural effectiveness of advertisements, aiding companies in developing more effective communication strategies in global markets.

ISC also has broad application prospects for social and team collaborations. By monitoring team members' ISC, ISC can evaluate the real-time effectiveness of teamwork, particularly during complex tasks or decision-making situations. For example, in corporate or research teams, ISC can be used to monitor and provide feedback on the state of team collaborations, identify potential issues, and make timely adjustments. ISC can also be potentially applied in psychotherapy and social-skills training, particularly or individuals with autism spectrum disorder, as it can provide valuable feedback, help to assess treatment outcomes, and adjust therapeutic methods [78].

Implementation challenges and solutions

Despite the potential of ISC as a tool in the attention research, its practical application faces several challenges. First, the complexity of experimental designs is a major issue. To accurately measure the relationship between ISC and attention, research needs to be conducted under highly-controlled experimental conditions while ensuring that the experimental scenarios are natural enough to capture real-life social interactions. Achieving this balance is often difficult, as overly strict controls may undermine the ecological validity of the experiment, whereas overly natural scenarios may introduce too many confounding variables, which affects the interpretation of the results. Second, data collection remains challenging. The ISC research typically relies on high-temporal-resolution EEG or high-spatial-resolution fMRI data, which require complex equipment and specialized technical support. Additionally, simultaneously recording brain activity from multiple individuals to ensure data synchronization and accurate processing increases the difficulty of data collection and analysis [79]. Therefore, researchers are exploring new technologies and methods to address these challenges. For example, by using multimodal data integration techniques that combine the strengths of

EEG and fMRI to provide a more comprehensive understanding of the relationship between ISC and attention by simultaneously recording high temporal and spatial resolution data [80]. Additionally, virtual reality technology offers the possibility of creating more natural experimental scenarios while maintaining strict control over experimental conditions. To solve data analysis difficulties, machine learning algorithms can be effective tools for handling large-scale complex data and enabling a more accurate identification and interpretation of the relationship between ISC and attention [78].

Misconceptions and advantages of scientific findings

Misconceptions

When exploring the relationship between ISC and attention, overinterpretation may lead to the misinterpretation and miscommunication of scientific findings. This risk primarily arises from two factors: the complexity and diversity of the research results, and the gap between the public's understanding and expectations of the research. The relationship between ISC and attention is not linear. Some studies [81] have demonstrated that inter-subject functional connectivity and intra-subject functional connectivity show only moderate correlation (mean rho = 0.34), suggesting these measures capture distinct neural processes rather than having a simple linear relationship. In reality, the relationship between ISC and attention is moderated by various factors, such as task type, social context, and individual differences [82, 83]. Therefore, using ISC as a direct indicator of attention may overlook these complex moderating factors, leading to misinterpreted research results [84]. For example, in some contexts, higher ISC may reflect emotional resonance or cognitive synchrony rather than attention concentration during social interactions.

In public communications, scientific conclusions are often simplified and drawn directly. When discussing the research on the relationship between ISC and attention, the media and public may overlook assumptions, limitations, and uncertainties, leading to misconceptions about the predictive power of ISC. ISC as a tool does not directly reveal specific cognitive mechanisms but provides a clue for exploring individual engagement or attention levels. To avoid misconceptions, researchers should emphasize the following critical aspects when exploring the relationship between ISC and attention. First, it is important to consider the context-specific nature of ISC because its relationship with attention can vary depending on the task type, emotional engagement, and social interaction context. Researchers should also highlight the multifactorial influences that modulate ISC, including individual differences, task complexity, and social dynamics and address the methodological limitations and potential confounding factors affecting the interpretation of ISC as a measure of attention. By thoroughly discussing these complexities and providing a nuanced analysis of the findings, researchers can ensure a more accurate understanding and application of ISC in the attention research. Doing so will contribute to the advancement of the knowledge in this field, avoid the pitfalls of oversimplification, and enhance the relevance of ISC as a predictive tool for attention.

Advantages of the ISC research in the study of attention

The ISC research offers a novel perspective for understanding the mechanisms of attention, particularly in the context of complex social interactions, where attention regulation is crucial. The traditional attention research [17] has often focused on cognitive processes at the individual level, whereas the ISC research extends this perspective by exploring how ISC among multiple individuals in joint tasks or interaction scenarios reflects and regulates attention. By simultaneously recording brain activity from multiple participants, the ISC research has revealed how individuals influence each other's attention levels during interactions. A significant advantage of this approach is its ability to capture attention dynamics in real-world social contexts. For example, in the educational setting, the ISC between teachers and students is considered the neural basis for effective teaching, suggesting that ISC levels significantly increase when students are highly focused [11]. This synchrony reflects individual attention states and reveals the potential influence of social interactions on attention regulation. Additionally, the ISC research can shed light on the distribution and coordination of attention in team collaborations, which can help to understand how team members achieve more effective cooperation through ISC [85]. The ISC research has also provided a unique opportunity to integrate individual cognitive processes with group-level interaction dynamics, leading to a more comprehensive understanding of how attention operates in complex social contexts [35]. This integration helps to uncover the fundamental mechanisms of attention and provides scientific evidence for improving its practical application, such as in the educational and teamwork contexts.

Future directions and optimization of the ISC research

Optimization of task design and cross-cultural applicability

The future research should explore how standardized experimental task designs and the integration of real-world scenarios can enhance the consistency and ecological validity of ISC measurements [86]. A standardized task design can ensure comparability across different studies, while the incorporation of real-world contexts can increase the ecological validity of the experimental results. Additionally, the future research should investigate the universality and effectiveness of ISC in different cultural contexts and educational systems, and should validate ISC as a potential global indicator of attention and engagement through cross-cultural research [87].

Technological advancements and multimodal integration

The future research should also focus on improving the applicability of ISC technology. With the technological innovations in data analysis techniques, the precision and scope of ISC measurements are expected to further advance [14]. Therefore, researchers should explore new measurement devices and real-time data processing algorithms to enhance the applicability of ISC in multitasking and multimodal environments. Moreover, integrating ISC with other neurophysiological indicators (e.g., GSR and HR variability) to build a more comprehensive cognitive state assessment system will help to better understand the neural mechanisms involved in complex cognitive and emotional processes, which can drive its future research and application in related fields [88].

Conclusion

We systematically reviewed the research on ISC as a predictive measure of attention and engagement. By analyzing studies conducted in laboratory and real-world settings, we found that ISC, particularly in the prefrontal and temporoparietal regions, was closely linked to attention and cognitive engagement levels during tasks. These brain areas play crucial roles in cognitive control and emotional resonance, which further supports ISC as a reliable indicator of cognitive load and emotional involvement during complex tasks. Certain challenges exist when applying neuroimaging technology, such as equipment complexity and data-processing difficulties. Nevertheless, these obstacles are gradually being overcome with technological advancements, especially due to the increased availability of portable EEG and functional near-infrared spectroscopy (fNIRS) devices [89]. Overall, ISC provides a novel approach for understanding the neural mechanisms underlying ISC during complex cognitive processes. Therefore, the future research should further explore ISC performance across different task types and in terms of individual differences to deepen the understanding of the neural mechanisms of attention and cognitive engagement [90], so as to provide new perspectives and theoretical support for the development of cognitive neuroscience. As the research progresses, ISC is poised to become a powerful tool for assessing the quality of individual cognitive states during social interactions, which can drive the advancements in related fields.

Abbreviations

ISC	Intersubject Correlation
EEG	Electroencephalography
fMRI	Functional Magnetic Resonance Imaging
BOLD	Blood-Oxygen-Level Dependent
ROI	Region of Interest
PLV	Phase-Locking Value
GSR	Galvanic Skin Response
HR	Heart Rate
MOOC	Massive Open Online Course
CB	Continuous Behavioral
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
REML	Restricted Maximum Likelihood
AUC	Area Under the Curve
DAN	Dorsal Attention Network
VAN	Ventral Attention Network
DMN	Default Mode Network
EDA	Electrodermal Activity
SA	Socially Arousing
AA	Affective Arousal

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Author contributions
Qing Liu, Yuhang Lin and Wenjuan Zhang made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas, took part in drafting, revising, or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Data availability
All data, models, and codes generated or used during the study appear in the submitted article.

Declarations

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Not applicable.

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