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Review

EEG Signal Processing Pipelines in the Study of Neurophysiological Characteristics of Gifted Primary School Children: A Scoping Review

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Abstract

This review systematically examines electroencephalography (EEG) studies on gifted children, focusing on the signal processing pipelines across acquisition, preprocessing, feature extraction, and analysis, and identifying opportunities for methodological standardisation relevant to educational research. Following PRISMA 2020 guidelines, a comprehensive search was carried out in PubMed, Scopus, Web of Science, IEEE Xplore, and PsycINFO. From 197 records, 14 studies met the inclusion criteria and were analysed for EEG setup, preprocessing strategies, and analytical approaches, including event-related potentials, spectral and connectivity measures, and applications of machine learning. Substantial heterogeneity was observed in device configurations, preprocessing practices, and analytical choices, limiting cross-study comparability and the transfer of findings to educational contexts. Nevertheless, recurring neurophysiological markers were identified, such as P300, frontoparietal γ synchronisation, and θ–α modulations during cognitive tasks. Only a minority of studies implemented supervised classification methods, suggesting an underexplored potential for advanced data-driven approaches in paediatric EEG. Transparent and standardised EEG pipelines, with explicit reporting of filters, artefact thresholds, and rejection rates, are essential to enhance reproducibility and translational value. By framing EEG signal processing within an educational perspective, this review provides methodological guidance to support early identification, inform classroom practice, and strengthen the bridge between neuroscience and education.

Keywords: gifted children; electroencephalography (EEG); EEG signal processing; feature extraction; neurocognitive efficiency; machine learning

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1. Introduction

Gifted students stand out for their exceptional academic, cognitive, and creative performance [1]. Renzulli (2011) [1] conceptualised giftedness as a combination of above-average ability, creativity and task commitment, which was later formalised in his three-ring model together with Piaget (2005) [2]. In parallel, Gagné (2004) [3] proposed the Differentiated Model of Giftedness and Talent, emphasising the developmental transformation of natural abilities into systematically trained skills. The identification of gifted children remains challenging, with prevalence estimates ranging from 2 to 3% using strict IQ-based criteria

to up to 10% when broader dimensions such as creativity or leadership are considered [4]. This conceptual variability underscores the need for complementary tools to obtain a more complete, objective understanding of giftedness. From a neuroscientific standpoint, Basso and Suzuki (2017) [5] reviewed how techniques such as EEG [6], fMRI and fNIRS can be used to study brain–behaviour relationships, and EEG has become particularly relevant in paediatric populations due to its non-invasiveness and high temporal resolution.

EEG research has provided meaningful insights into cognitive functioning in gifted populations. Folstein and Van Petten (2008) [7] described how the N200 component is linked to conflict detection and cognitive control, while Polich (2007) [8] proposed an integrative theory of the P300, relating it to attentional allocation and context updating. Other components such as the mismatch negativity (MMN) [9] and the LPC/P600 [10] have been used to characterise early sensory discrimination and later stages of information integration. In the context of giftedness, Jaušovec (1997, 2000) [11,12] reported differences in α activity and cognitive processing between gifted and non-identified individuals, while Alexander et al. (1996) [13] and later works such as those of Zhang et al. (2014) [14] and Wei et al. (2020) [15] examined oscillatory activity and connectivity in mathematically gifted adolescents. Schack et al. (2001) [16] analysed coherence patterns and microstates, suggesting more efficient neural synchronisation, and Shen et al. (2024) [17] proposed an EEG–behavioural framework to explore psychophysiological patterns underlying academic performance in gifted students. In parallel, Bomatter et al. (2024) [18] showed how modern machine learning methods can learn brain-specific biomarkers from EEG, illustrating the potential of AI-based approaches for extracting complex neural patterns.

Despite these developments, the current literature on EEG in gifted children exhibits substantial methodological variability. Studies differ widely in acquisition parameters (e.g., number of channels and sampling rates), preprocessing steps (e.g., filtering, artefact handling, and segmentation), feature extraction techniques, and subsequent statistical or ML analyses. This heterogeneity reflects the absence of standardised EEG pipelines and limits the comparability and reproducibility of findings. Kuznetsova et al. (2024) [19] recently provided a systematic review of cognitive, physiological and psychological characteristics of gifted children, but the technical and engineering aspects of EEG processing received far less attention. As a result, it remains unclear how methodological decisions affect reported neural patterns or how EEG evidence can be meaningfully synthesised across studies.

For these reasons, it is necessary to review not only the outcomes of prior research but also the methodological strategies implemented at each stage of EEG processing. Accordingly, the present scoping review synthesises the methodological approaches used to acquire, preprocess, extract features from and analyse EEG signals in studies involving gifted children. By identifying methodological patterns, inconsistencies and gaps, this work seeks to provide a clearer foundation for more transparent, consistent and reproducible EEG pipelines in giftedness research. The article is structured as follows: Section 2 describes the methodology based on the PRISMA framework; Section 3 summarises the characteristics of the selected studies; Section 4 discusses the technical strategies employed across the literature; and Section 5 presents the main conclusions and directions for future research.

2. Materials and Methods

This scoping review was designed and conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework guidelines [20]. The main objective was to analyse the existing literature on the use of EEG in a specific context: the study of the neurophysiological characteristics of gifted children processed through signal processing pipelines, including acquisition, preprocessing, filtering, feature

extraction, and feature selection, followed by advanced analysis with machine learning, deep learning, and other related methods.

2.1. Search Strategy and Screening Procedure

To ensure methodological transparency and reproducibility, the search strategy and screening process were explicitly defined a priori according to PRISMA guidelines. The search combined terms related to EEG, giftedness, and children using Boolean operators: ("EEG" OR "Electroencephalogram") AND ("gifted" OR "high-ability" OR "talent*") AND (child* OR "primary school"). The query syntax was adapted for each database to maintain equivalence in search coverage. Representative examples include the following:

- PubMed: ("electroencephalography" OR "EEG") AND ("gifted children" OR "high-ability children" OR "giftedness") AND ("signal processing" OR "machine learning" OR "artificial intelligence").
- Scopus/Web of Science: TITLE-ABS-KEY (("EEG" OR "electroencephalogram") AND ("gifted*" OR "high-ability" OR "talent*") AND ("signal processing" OR "machine learning" OR "neural")).
- IEEE Xplore: ("EEG" AND "gifted*" AND ("feature extraction" OR "preprocessing")).
- PsycINFO: ("EEG" OR "brain activity") AND ("gifted children" OR "giftedness").

All retrieved records were exported to a reference manager (Zotero), and duplicate entries were removed by automated DOI matching followed by the manual verification of titles and authors. Titles and abstracts were independently screened by the authors to identify potentially eligible studies, with disagreements resolved through consensus.

Only peer-reviewed journal articles were retained, while gray literature (conference proceedings, preprints, or non-indexed sources) was excluded to maintain methodological rigour. A qualitative bias assessment was also conducted, focusing on (i) clarity in defining giftedness, (ii) transparency in EEG acquisition and preprocessing reporting, and (iii) adequacy of the analytical approach. Given the heterogeneity and limited number of studies, formal inter-rater reliability statistics or quantitative bias tools were not applied.

Finally, the review protocol was not preregistered in databases such as PROSPERO or OSF; however, all methodological steps—including search period, inclusion/exclusion criteria, and extraction procedures—were predefined by the authors to ensure transparency and replicability.

To achieve this, an exhaustive search was conducted in the following databases: PubMed, Scopus, Web of Science, IEEE Xplore, and PsycINFO. The search was carried out between October 2024 and October 2025. These databases were selected due to their broad coverage of academic literature in fields related to neuroscience, engineering, technology, and education, making them essential sources for identifying relevant studies in the context of this review. In addition, secondary engines such as Google Scholar and ResearchGate were also explored. However, all results obtained through these engines were discarded due to being duplicate publications or studies that did not meet the established inclusion criteria, thereby reinforcing the focus on official and high-quality sources. Although grey literature was excluded, full peer-reviewed conference papers indexed in major academic databases (e.g., IEEE) were retained when they provided complete methodological information and original EEG data relevant to the study objectives.

Based on this search, the inclusion and exclusion criteria were as follows:

- Inclusion criteria:
  - Original peer-reviewed studies.
  - Research using EEG as the primary tool to analyse brain activity.

  - Articles examining the neurophysiological characteristics of gifted children using classical statistics, Machine Learning or other related methods.
  - Publications including samples of children aged between 5 and 13 years.
- Exclusion criteria:
  - Narrative reviews or editorials.
  - Studies focused on adults or outside the specified age range.
  - Research that did not explicitly mention EEG and giftedness as key variables.
  - Articles that did not provide complete information on methods or results.

2.2. Study Selection and Data Extraction

The selection process followed PRISMA recommendations. In the first phase, titles and abstracts were reviewed to exclude irrelevant records. Full-text assessment was conducted for potentially eligible studies according to the predefined criteria. Data extraction was carried out using a standardised template, including publication details, sample characteristics, EEG setup (channels, sampling rate, and reference), preprocessing pipeline (filtering parameters, artefact handling, and rejection thresholds), and analytical approach (ERP, spectral, or machine learning). This structured approach ensured consistency across studies.

The article selection process was carried out in three stages. In the first stage, the titles and abstracts of the articles were reviewed to identify potentially relevant studies, followed by a full-text review in the second stage to confirm their eligibility according to the established criteria. Figure 1 shows the PRISMA diagram summarizing the different search and filtering stages. Finally, in the third stage, the selected studies underwent a detailed analysis, and key data were extracted, including the authors, year and country of publication, study design and sample, the methods used to record and analyse brain activity using EEG, the main findings related to giftedness, and the conclusions relevant to the integration of EEG in this field. All extracted information was organised into summary tables to facilitate analysis.

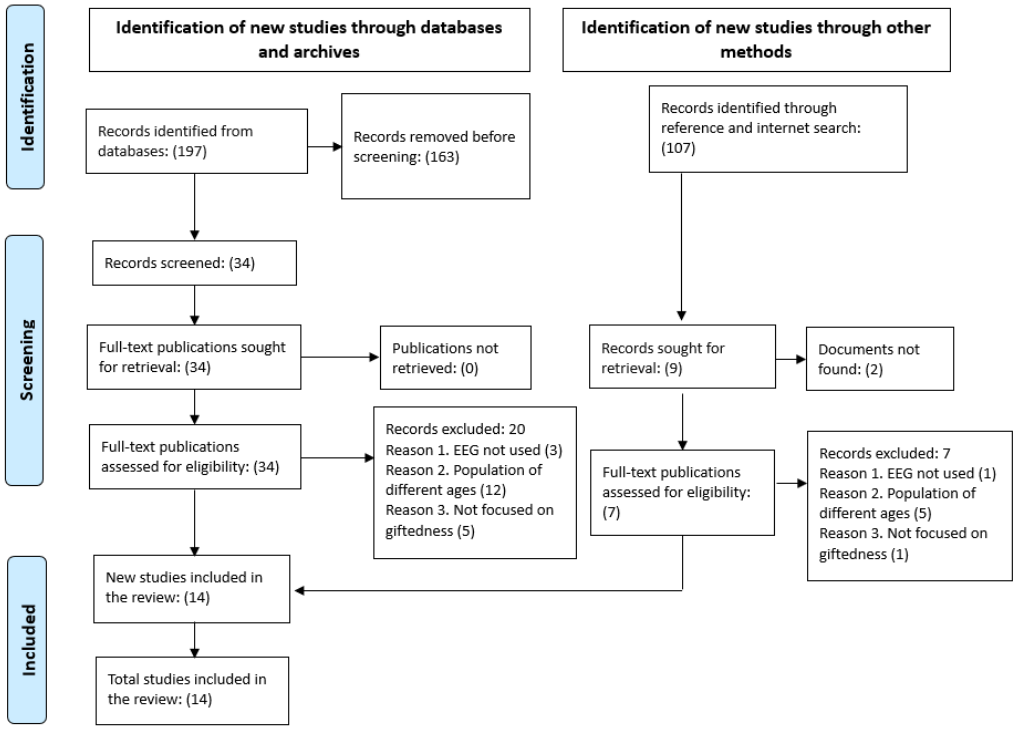


Figure 1. PRISMA diagram [20].

2.3. Risk of Bias and Quality Appraisal

A structured narrative appraisal was conducted to identify potential methodological limitations and sources of bias among the included studies. Each article was qualitatively examined across three domains: (i) clarity in defining giftedness and inclusion criteria, (ii) transparency and completeness in reporting EEG acquisition and preprocessing parameters, and (iii) adequacy of analytical and statistical methods.

Although formal scoring tools such as RoB 2 or QUADAS-2 were not applied due to the small and heterogeneous corpus, the evaluation followed the conceptual logic of these frameworks—focusing on reproducibility and reporting quality. Overall, most studies provided sufficient information about EEG acquisition (e.g., electrode montage and sampling rate) but were less consistent in describing preprocessing details such as filter parameters, artefact correction methods, or amplitude thresholds. In several cases, the reference scheme or rejection criteria were not explicitly stated.

This qualitative appraisal suggests that the general methodological quality of the reviewed studies is acceptable but limited by incomplete reporting, which constrains direct cross-study comparisons. None of the included studies were excluded based on quality assessment, but these limitations were considered when interpreting the evidence. Future reviews would benefit from the adoption of a standardised quality checklist specifically tailored to EEG-based paediatric and educational research.

A total of 197 records were retrieved from the selected databases (PubMed = 26, Scopus = 42, Web of Science = 115, IEEE Xplore = 10, PsycINFO = 4). In addition, 107 further records were identified through reference lists and external searches (Google Scholar, ResearchGate, SpringerLink), but these were processed separately. During the initial screening phase, 163 of the 197 database records were excluded after inspection of title and abstract. The reasons for exclusion were the absence of at least one of the main criteria, such as the use of EEG as the primary tool, the inclusion of gifted or high-ability populations, or the appropriate age range. This step corresponds to the identification stage of the PRISMA process and ensured that only potentially eligible articles were considered for full-text assessment. After this refinement, 34 database articles and 7 from other sources were evaluated in full text. Of these, 20 were excluded for specific reasons (n = 3 no EEG, n = 12 inappropriate age, n = 5 not focused on giftedness). Ultimately, 14 studies met all criteria and were included in this scoping review (Figure 1).

Lastly, this study acknowledges the limitations related to the heterogeneity of EEG methods employed in the selected studies, which complicates a direct comparison and integration of results. Additionally, there are still relatively few studies that solidly combine neuroscience, specifically EEG, with the study of intellectual giftedness in school-aged children. This highlights the need for a scoping review that synthesises the existing literature with the aim of identifying consistent patterns in brain activity and their relationship with higher cognitive ability.

In this context, the present review aims not only to assess current findings but also to provide a solid foundation for future studies. By addressing these methodological and conceptual gaps, it is expected to move toward a more comprehensive understanding of the role of EEG in the identification and analysis of giftedness in primary school students. Moreover, this approach seeks to lay the groundwork for the design of educational interventions based on neuroscientific evidence, thereby improving the support and development of these students in academic settings. The structuring of the extracted data and its detailed analysis reflect this review's commitment to a rigorous and unified approach that contributes to closing the existing gaps in the current literature.

3. Results

The studies gathered reflect a clear effort to characterize the neurophysiological particularities of gifted children using EEG, and this scoping review organises and analyses these works to better understand the specific patterns of brain activity that distinguish this population. The collected information encompasses a variety of methodologies, ranging from event-related potential (ERP) analyses—also referred to as evoked potentials—to studies centred on functional connectivity and neural efficiency. Taken together, these approaches help identify key differences between gifted children and their neurotypical peers, particularly regarding brain activation during complex tasks and the optimisation of cognitive resources. Table 1 synthesises the main findings derived from the PRISMA study, organizing the articles according to their objectives, employed methods, sample characteristics, and most relevant results. This analysis seeks not only to provide a clear overview of the current state of research but also to highlight its most significant aspects, thereby offering useful guidance for future studies in the field.

The studies analysed in this scoping review have revealed multiple relevant findings regarding the neurophysiological characteristics of gifted children, as assessed through electroencephalography technologies. These investigations highlight significant differences in neural connectivity, brainwave band synchronisation, and responses to specific tasks, reinforcing the notion of greater neural efficiency in this population. It is important to note that these findings are derived from a limited set of 14 studies that met strict inclusion criteria. As such, the patterns described below should be interpreted as recurrent trends within this specific body of evidence rather than as definitive universal markers of giftedness.

Synthesis of EEG Pipelines Across Studies

A cross-comparison of the 14 reviewed studies reveals both common methodological structures and substantial variability across acquisition and preprocessing pipelines. Regarding the recording setup, the majority employed between 9 and 32 electrodes using the international 10/20 system, although some high-resolution works used up to 64 channels (e.g., Zhang et al., 2014 [14]; Wei et al., 2020 [15]), and one recent study adopted a four-channel portable device (Ghali et al., 2019 [21]). Sampling frequencies ranged from 100 Hz to 1000 Hz, with 500 Hz being the most typical value. Nearly all studies applied conductive gel electrodes, while only one explicitly tested low-density/portable systems, underscoring a predominance of traditional laboratory-based EEG. None of the reviewed studies reported the use of dry or semi-dry electrodes; all relied on conventional wet Ag/AgCl systems within the standard 10–20 configuration. While these setups ensure signal quality, they limit the ecological applicability of EEG in educational contexts due to longer preparation times and the need for conductive gel. Future research should explore dry and semi-dry technologies, which can substantially improve the portability, comfort, and feasibility of EEG data collection in real-world school environments.

In terms of hlfiltering and artefact handling, the most recurrent configuration involved band-pass filters within approximately 0.1–40 Hz, often complemented by a 50 Hz notch filter. However, cut-off choices were not uniform: for instance, Alexander et al. (1996) [13] reported 0.3–60 Hz, whereas Benharrath et al. (2020) [22] restricted activity to 0.1–3 Hz to isolate slow semantic components. Artefact correction methods ranged from Independent Component Analysis (ICA) or regression-based ocular removal (e.g., Duan, 2009 [23]; Wei, 2020 [15]) to purely manual/visual trial rejection in earlier works. Rejection thresholds typically fell between $\pm 50\ \mu V$ and $\pm 150\ \mu V$, and several studies required at least 16–32 s of artefact-free EEG per condition for analysis. These parameters directly affect signal-to-noise ratio and, therefore, comparability.

Table 1. Summary of EEG studies in gifted children.

Article	Recording Setup	Preprocessing	Analysis Approach	Sample	Main Findings
[22]	32 channels (10/20), 1000 Hz; fixation task	Minimum 32 s artefact-free EEG; band-pass 0.1–3 Hz; manual rejection	ERP (N400) via Integral Shape Averaging (ISA) vs. classical SSA	3 gifted children (8–12 y/o, mean = 9.6), right-handed, native French speakers, WISC IQ $>$ 140	Greater N400 amplitudes at C3 and Cz using ISA; enhanced ERP visibility with fewer trials compared to SSA.
[24]	9 channels (10/20), 500 Hz; task-switching (single vs. mixed blocks); EEG amplified by SynAmps 2 online	Regression-based ocular artefact removal; 1200 ms epochs (200 ms baseline); trials exceeding $\pm$50 µV rejected; only correct trials analysed	Amplitude and latency analysis of P300 across conditions	26 children (13 gifted, 13 average), all 12 y/o	Gifted children showed faster responses and P300 modulation by condition, suggesting earlier cognitive maturation and enhanced executive control.
[13]	8 channels (F1, F2, T7, T8, P3, P4, O1, O2), 100 Hz; eyes-open fixation; linked ears	Visual inspection; removal of blinks/EMG $>$ 50 µV; $\geq$32 s clean EEG; α power (8–12 Hz) log-transformed	α power quantification; interhemispheric ANOVAs	90 participants: 30 gifted (13 y/o), 30 average (13 y/o), 30 college (20 y/o); all right-handed	Gifted had lower α than average but similar to college; greater RH α vs. LH (temporal/parietal), suggesting adult-like cortical organisation.
[25]	16 channels (10/20), 256 Hz; linked ears; impedance $<$ 5 kΩ; Rest (fixation) vs. Quail Egg Task	$\geq$16 s artefact-free segments; band-pass 0.3–60 Hz; visual rejection of artefacts	Averaged cross-mutual information (A-CMI); *t*-tests and ANOVAs across electrode pairs	50 children (25 gifted, 25 average), age $\approx$ 11; gifted: IQ $>$ 130 + creativity test (TCT $>$ 119)	Gifted showed higher A-CMI in left temporal-central, temporal-parietal, and central-parietal, more efficient posterior information transmission.
[26]	16 channels (10/20), 256 Hz; linked ears; impedance $<$ 5 kΩ; rest (eyes closed, 1 min) vs. ROCF memorizing (1 min)	Band-pass 0.3–60 Hz; visual rejection of artefacts; 16 s for analysis	Functional cluster (CI) and neural complexity (CN); topographic cluster maps; ANOVAs and *t*-tests ($p < 0.05/0.01$)	36 middle school students (18 gifted, 18 average), all right-handed, 13 years old	Gifted showed higher recall and neural complexity during ROCF; FC maps revealed stronger right temporal–occipital, bilateral prefrontal cooperation, right dominance.

Table 1. *Cont.*

Article	Recording Setup	Preprocessing	Analysis Approach	Sample	Main Findings
[15]	60 channels (10/20), 1000 Hz; deductive reasoning task (25–30 min); cortical source localisation (Brainstorm, 256 ROIs)	Baseline correction; ocular artefact removal with ICA (EEGLab); band-pass 1–60 Hz; projection of sensor data to cortical dipoles	Granger causality; graph theory (causal density, characteristic path length); θ/γ bands; ANOVA	38 adolescents (20 gifted, 18 controls); high math ability; Raven's > 32	Gifted showed higher accuracy and faster RTs; stronger θ-band working memory processing; more efficient frontoparietal connectivity; reduced parietal flow in conclusion phase, suggesting automatised reasoning.
[23]	10 channels (10/20), 500 Hz; shielded, sound-attenuated room; impedance < 5 kΩ	Regression-based ocular artefact removal (Neuroscan); band-pass 0.05–100 Hz; 1200 ms epochs (200 ms baseline); exceeding ± 50 µV rejected; only correct trials analysed	ERP analysis of N2 (200–380 ms) and P3 (300–500 ms) in Go/NoGo task; ANOVA by group at Fz, Cz, Pz	30 children (15 gifted, 15 average), ≈ 12 y/o; matched by age/sex; gifted: higher Raven's scores	Gifted showed fewer errors and shorter P3 latencies (Go and NoGo), indicating faster response evaluation/inhibition; N2 latency unaffected by intelligence.
[27]	32 channels (10/20), 500 Hz; auditory oddball; shielded room; Ag/AgCl electrodes	Empirical Mode Decomposition (EMD) applied to single-trial EEG (Fz, Cz), band-pass 0.3–30 Hz;	P300 extraction with EMD; 10 statistical features; Characterisation Degree (CD-J) for feature selection	20 participants: 10 gifted (8–13 y/o, IQ > 140) and 10 adults (42–50 y/o), all right-handed, normal vision/hearing; some parent–child pairs	Gifted children showed stronger and more distinct P300 features. Five features (RMS, variance, range, 4th moment, IQR) were optimal for group differentiation.
[28]	3 channels (Fz, Cz, Pz), BRAIN QUICK EEG, 1024 Hz; auditory oddball; binaural tones; 15 deviants per ERP	Artefact rejection threshold ± 150 µV; band-pass 0.1–30 Hz;	Amplitude/latency analysis of MMN (Fz) and P300 (Pz); correlations with social cognition and perfectionism	43 children (16 HIP, 17 HFA, 10 NTD), 6–16 y/o; HIP: IQ $>$ 95th percentile; full neuropsychological profiles	MMN amplitude normal in HIP, reduced in HFA; no P300 differences. In HIP group, poorer social cognition correlated with delayed MMN latency. MMN could help differentiate HIP from HFA.

Table 1. *Cont.*

Article	Recording Setup	Preprocessing	Analysis Approach	Sample	Main Findings
[29]	32 channels (10/20), 500 Hz; shielded room; matching vs. mismatching (2-back)	Ocular regression (Neuroscan); 1200 ms epochs (200 ms baseline); band-pass 0.05–100 Hz; $\pm$50 μV rejection; correct trials only	Amplitude/latency analysis of P2, N2, LPC; repeated-measures ANOVA (group $\times$ condition $\times$ site)	30 children (15 gifted, 15 average), $\approx$ 12 y/o; right-handed, normal vision; gifted: higher Raven's SPM	Gifted were more accurate and showed larger LPC amplitudes under matching condition, supporting neural efficiency; no group differences in P2/N2.
[30]	64 channels, 500 Hz; visual search with Chinese words, English letters, Arabic numbers; shielded room; impedance < 5 kΩ	PCA ocular correction; band-pass 0.01–30 Hz; baseline $-$200 ms; windows (200–300, 300–500, 500–800 ms)	ERP components (N125, P220, N370, P600); repeated-measures ANOVAs; topographic mapping	28 children (15 gifted, 13 average), mean age $\approx$ 11.7; gifted $>$95th percentile, accelerated program	Gifted showed higher accuracy, shorter P600 latencies and larger amplitudes, especially in Chinese word tasks; more neural efficiency and coordinated neural networks.
[31]	9 channels, 500 Hz; 1-back working memory (3 trial types); linked ears; impedance < 5 kΩ	Manual artefact rejection; Ocular regression (Neuroscan); baseline-corrected epoch; band-pass (not reported)	ERP analysis of P3 component (amplitude, latency) across trial types	26 children (13 gifted, 13 average), all aged 12; gifted identified via IQ and creativity	Gifted showed shorter P3 latency and faster responses, indicating greater neural efficiency in working memory.
[32]	19 channels (10/20), 1000 Hz; shielded/soundproof room	900 ms epochs ($-$100 to 800 ms); baseline $-$100 ms; band-pass 0.05–100 Hz; artefact rejection $\pm$100 μV	ERP analysis: MMN, LDN, eMMN, P3a; mixed ANOVAs; deviant–standard and novel–standard difference waves	36 children (18 gifted, 18 average), mean age $\approx$ 11.8; gifted $>$95th percentile IQ + multi-criteria selection	Gifted showed larger MMN, LDN, eMMN, P3a amplitudes and shorter LDN latency, supporting neural efficiency and speed of intelligence hypotheses.
[21]	4 channels; NetMath math tasks; sampling rate not reported	EEG mental states (attention, relaxation, workload); 5 stats per state; synchronised with task performance	Classification with J48, Bagging, Adaïve Bayes; 10-fold CV; resampling to balance classes	17 students (M=10.05, 4th–5th grade); gifted = score $>$ group mean (59.6%)	Best model J48 (76.9% accuracy); strongest predictors were "Strong student" status and relaxation; lower attention linked to non-gifted.

With respect to epoching and baseline correction, ERP-focused studies commonly segmented trials into 800–1200 ms windows and applied baseline correction in the −200 ms pre-stimulus interval, whereas functional connectivity or resting-state analyses worked with continuous windows (16–60 s) rather than discrete epochs, reflecting their distinct aims: time-locked cognitive evaluation versus large-scale network organisation. In terms of software/toolchains, several studies reported using established EEG environments such as EEGLAB, BrainVision Analyzer or Brainstorm for preprocessing, source modelling, or connectivity estimation, while others relied on custom scripts (e.g., empirical mode decomposition for P300 extraction). However, reporting was inconsistent, as the reference montage, percentage of rejected trials, and exact preprocessing order were not always specified. Overall, the reviewed literature converges on a broadly similar conceptual pipeline (acquisition → preprocessing → feature extraction → analysis), but the concrete parameterisation of each step varies markedly across studies. Making these parameters explicit helps clarify why cross-study quantitative comparison remains difficult and further motivates the need for minimum reporting standards in future paediatric giftedness EEG research.

EEG Characteristics

Across the reviewed studies, EEG systems ranged from very low-density configurations (3–4 channels) to high-density setups with up to 64 electrodes. Classical ERP investigations typically used low- to medium-density montages between 9 and 32 channels for components such as P300, N400, MMN, LDN, P2 or LPC [22–24,27–29,31,32]. One ERP study employed a 64-channel system to obtain detailed topographic information during visual search tasks [30]. In contrast, connectivity-oriented analyses used either intermediate densities (16 channels for cross-mutual information [25]) or high-density systems (60 channels for Granger-causality modelling [15]). Additional low-density approaches included 8-channel spectral power work [13] and a 4-channel portable mental-state classifier [21]. Sampling frequencies varied between 100 and 1000 Hz, with lower rates applied in spectral and connectivity analyses and higher rates used for ERP studies requiring precise latency estimation [27,29,32]. Most setups adhered to the international 10–20 system [22,23], ensuring replicability across laboratories.

Despite this heterogeneity, the diversity of channel counts, sampling rates and hardware types is not unexpected since EEG research more broadly has progressively expanded beyond laboratory-grade systems. Multiple fields—including mobile BCIs, emotion recognition, and clinical monitoring—have shifted toward low-density, wireless, and portable EEG technologies that support real-world data collection [33]. Giftedness research is beginning to follow this trajectory: Shen et al. [17] recently employed a portable EEG-based real-time intelligence evaluation framework, illustrating the feasibility of classroom-ready systems. This trend suggests that, although most current studies still rely on conventional equipment, the transition toward mobile, school-friendly EEG acquisition is both anticipated and aligned with developments across the broader EEG community, offering promising avenues for future research and ecological implementation.

Preprocessing and Feature extraction

A key methodological aspect across the reviewed literature is the diversity of EEG preprocessing pipelines. Studies consistently included band-pass filtering, ocular artefact correction (regression or ICA), segmentation into epochs, and rejection of trials exceeding amplitude thresholds (ranging from ±50 μV to ±150 μV). Some works required a minimum of 16–32 s of artefact-free EEG for analysis [25], while others restricted analyses to correct trials only [23]. Advanced methods such as empirical mode decomposition (EMD) [27] or principal component analysis (PCA) [24] were employed to optimize ERP detection and feature selection. However, the lack of standardised pipelines limits reproducibility and complicates cross-study synthesis. From an engineering standpoint, promoting harmonised

preprocessing standards—including clear reporting of filter parameters, artefact thresholds, and reference schemes—would increase the robustness of findings and their applicability to clinical or educational contexts. To clarify the role of ICA, although this method can theoretically attenuate multiple artefact sources (ocular, muscular, cardiac or line-noise components), in the studies included in this review ICA was used exclusively for ocular artefacts. None of the reviewed works reported ICA-based correction of EMG, ECG or environmental noise, and no mobile or classroom-based recordings required additional movement-related artefact procedures.

A major limitation observed across the reviewed studies is the strong heterogeneity in preprocessing settings. Although all works included basic filtering and artefact removal, the specific parameters varied substantially, with cut-off frequencies ranging from narrow to broad bands and artefact thresholds spanning from $\pm 50\,\mu V$ to $\pm 150\,\mu V$. These choices directly affect the signal-to-noise ratio and the number of usable epochs, making results difficult to compare across studies. Similarly, the choice of artefact handling method—regression, ICA, or visual inspection—can yield different balances between neural preservation and noise suppression. This variability also constrains the extent to which common "signal-processing markers" can be asserted across studies; where convergences are described (e.g., P300 differences), they should be interpreted as recurring tendencies rather than diagnostic criteria. Regarding feature extraction, the reviewed literature primarily relied on classical approaches. ERP-based studies extracted amplitude and latency measures from components such as N200, P300, MMN or LPC; spectral analyses quantified band-power in α, θ or γ ranges; and connectivity-focused works computed metrics such as averaged cross-mutual information or graph-theoretic indices. Decomposition-based features appeared in isolated studies employing EMD or PCA. No deep learning approaches were present in the included corpus, which explains the absence of DL-driven feature extraction pipelines in this section.

Across the reviewed corpus, preprocessing and filtering strategies showed partial convergence despite the overall heterogeneity. Most studies applied a band-pass filter between 0.1 and 40 Hz, often with a 50 Hz notch to suppress power-line noise, and rejected epochs using thresholds typically between ± 75 and $\pm 120\,\mu V$, with at least 16–30 s of artefact-free data required per condition. Ocular and muscular artefacts were primarily corrected using ICA in studies employing EEGLAB or BrainVision Analyzer, while older works relied on regression or manual inspection. Recent developments have focused on improving artefact correction for naturalistic and wearable EEG: Ronca et al. [34] proposed *o-CLEAN*, a multi-stage ocular-artefact algorithm for out-of-the-lab recordings, and Kobler et al. [35] introduced a corneo-retinal-dipole and eyelid-related correction framework applicable both online and offline. Only three studies explicitly reported baseline correction windows (typically -200 ms to stimulus onset), and fewer than half detailed the reference scheme (average or linked mastoids). While parameter ranges vary, the underlying steps—filtering, segmentation, artefact correction, and epoch rejection—follow a broadly consistent conceptual pipeline, and making these settings explicit contributes to methodological transparency and future reproducibility.

Neural Connectivity

Gifted children exhibit lower but more localised activation in their neural networks, demonstrating a more efficient distribution of cognitive resources [25]. It was found that frontoparietal regions show more efficient neuronal communication, optimizing the use of brain resources and reducing cognitive load. These studies [15,25] performed mutual information analysis to evaluate functional connectivity between specific brain regions. In this context, mutual information is defined as a metric that quantifies the amount of information shared between two distinct systems, allowing for the prediction or extraction

of relevant data from one based on the other. In EEG analysis, this measure is used to determine connectivity between electrodes placed on different scalp areas, providing an accurate representation of interaction between brain regions.

One of these studies, ref. [15], states that such connectivity facilitates information integration and processing during demanding tasks. Based on the data collected, it developed effective connectivity techniques such as Granger causality analysis to identify the direction and magnitude of neural interactions, highlighting greater coordination between frontal and parietal networks in gifted children. Although these findings suggest a pattern of frontoparietal efficiency in gifted children, they are reported in a small number of studies with relatively modest sample sizes. Therefore, they should be interpreted as preliminary evidence that motivates future connectivity-oriented work, rather than definitive proof of a universal connectivity phenotype in giftedness.

Frequency Band Activation

Several reviewed studies [13,15] highlight significant differences in the power and activation of brainwave bands between gifted children and their average peers, associated with their exceptional cognitive performance. In particular, the α (8–12 Hz), θ (4–8 Hz), and γ (>30 Hz) bands stand out as key indicators across various cognitive contexts [13]. Gifted children show greater α band activation in frontal and occipital regions, which indicates a higher capacity to inhibit irrelevant stimuli during demanding cognitive tasks. This pattern has been linked to neural efficiency, as it allows more focused and effective information processing [13]. It is important to clarify, however, whether these results refer to absolute α power at rest or to event-related synchronisation/desynchronisation during tasks since each phenomenon has distinct functional implications.

During deductive reasoning tasks, an increase in θ band power has been observed in frontoparietal networks, supporting more efficient working memory and rapid, adaptive cognitive processing, as θ oscillations are considered essential for information integration under complex cognitive demands [15]. Likewise, in mathematical contexts, increased γ band activity has been reported—particularly in right-hemisphere regions involved in problem-solving—supporting the idea that gifted children optimize their neural resources through localised and efficient activation [14]. Taken together, findings in the α, θ, and γ bands recur across several studies but given the limited number of available works, they should be interpreted as promising neurophysiological tendencies rather than established or generalised biomarkers.

Event-Related Potential (ERP) Responses

The vast majority of studies focus on the analysis of evoked potentials, consistently reporting significant differences between gifted children and their average peers and identifying recurring patterns in cognitive processing. Numerous works have found higher amplitudes and shorter latencies in the P300 component, suggesting more efficient processing of relevant stimuli [24,27,29–31]. These investigations employed a range of methodological strategies, such as visual Go/NoGo paradigms, principal component analysis (PCA) [24], task-switching paradigms [29], working-memory evaluations [31], and visual search tasks [30]. More advanced techniques, including empirical mode decomposition (EMD), were also applied to optimize P300 detection and statistical feature selection [27]. Collectively, these approaches have helped identify distinctive ERP patterns that may contribute to understanding the enhanced cognitive performance observed in gifted children.

Beyond the P300, several studies analysed other evoked potentials to further characterize neurophysiological differences in this population. Greater N400 amplitudes have been reported in gifted children, suggesting more efficient semantic processing [22], while auditory paradigms examining the mismatch negativity (MMN) indicated higher ampli-

tudes in gifted participants compared to their peers [28]. These findings point to potential differences in auditory discrimination and sensory processing. Similarly, ref. [31] found that gifted children exhibited higher LPC amplitudes and greater response accuracy, which may reflect more efficient allocation of cognitive resources during tasks requiring sustained attention and cognitive control. Complementing these results, ref. [32] examined both MMN and P300, reporting greater amplitude and shorter latency in gifted children, reinforcing the notion of increased neural efficiency during auditory information processing. Taken together, these ERP findings recur across independent studies, although their interpretation should remain cautious given the limited number of paradigms and sample sizes.

To complement the methodological synthesis and facilitate visual understanding of the most recurrent EEG results, Figure 2 presents a representative ERP waveform illustrating the P300 component. This schematic example reflects one of the most consistently reported findings throughout the reviewed literature, highlighting the relevance of latency and amplitude differences as potential indicators of neural efficiency in gifted children. Although promising, these results should be viewed as converging but preliminary evidence that requires further replication before being considered robust biomarkers.

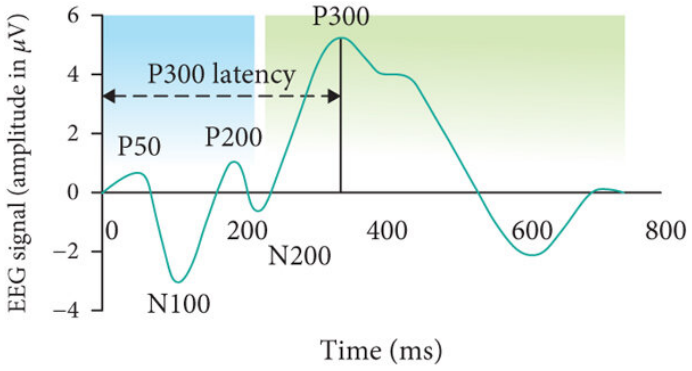


Figure 2. Representative event-related potential (ERP) waveform illustrating the P300 component, a recurrent finding across the reviewed studies [36].

Machine Learning

Although "Machine Learning" was included as a search term in the review protocol, the systematic screening revealed that only one of the fourteen included studies (Ghali et al. [21]) implemented a genuine machine learning classification framework based on EEG features. The remaining studies relied exclusively on classical statistical analyses of ERPs (e.g., amplitude and latency of P300, N400, and MMN) or spectral/connectivity measures, without using ML algorithms or predictive modelling. Therefore, contrary to the expectation suggested by the reviewer, the body of EEG research on gifted children does not commonly incorporate classification or supervised learning methods, which limits the degree to which cross-study ML comparisons can be conducted.

In Ghali et al. [21], a four-channel portable headset (Neeuro Senzeband) was used to derive mental-state indices of attention, workload, and relaxation while 17 students solved mathematics problems. For each exercise, five statistical descriptors per state were extracted (mean, median, standard deviation, minimum, and maximum), along with demographic and performance-related variables (age, difficulty level, score, "strong student" status, and response time). This yielded 143 labelled instances classified as gifted or non-gifted based on performance thresholds. Four supervised algorithms were evaluated using 10-fold cross-validation: J48 decision trees, Naïve Bayes, Bagging, and AdaBoost. On the original imbalanced dataset (100 "Yes" vs. 43 "No"), AdaBoost achieved the highest accuracy (70.63%), whereas J48 obtained 65.04%. However, F-measures for the non-gifted class remained below 0.44 across all models due to class imbalance. After applying oversampling

to balance the dataset, J48 became the best-performing classifier (76.88% accuracy), with attention and relaxation emerging as the most relevant EEG-derived predictors. The authors explicitly noted that these findings are preliminary and not suitable for screening or diagnostic purposes due to the small sample size and single-cohort design. Since none of the remaining thirteen studies implemented ML pipelines, a numerical comparison of classification performance across studies is not methodologically feasible.

Finally, no deep learning approaches were identified in the reviewed literature, and none of the studies used end-to-end modelling or architectures designed to reduce preprocessing demands. The scarcity of ML-based research in the field highlights a key gap: although EEG provides rich, high-dimensional data suitable for AI-driven analysis, the existing literature remains limited to traditional ERP and spectral methods. Future research should therefore explore more robust ML or DL pipelines, incorporate larger datasets, and adopt standardised validation strategies to enhance generalizability and reduce overfitting.

Toward Standardised Reporting

To transform the identified heterogeneity into actionable methodological guidance, Table 2 proposes a concise reporting framework. This checklist synthesises the most recurrent methodological variables observed across the reviewed studies and defines a minimum set of elements that should be consistently reported in future EEG research on giftedness. It aims to promote transparency, reproducibility, and cross-study comparability, aligning this emerging field with best practices in neuroengineering and educational neuroscience.

Table 2. Proposed minimum reporting checklist for EEG studies in giftedness research.

Pipeline Stage	Recommended Reporting Elements
Acquisition	Number of channels and 10/20 locations used; sampling frequency; amplifier type; reference montage (e.g., linked mastoids, average); impedance thresholds; recording condition (resting/task-based); environment description (shielded, classroom).
Preprocessing	Band-pass and notch filter settings; artefact correction/removal (e.g., ICA, regression, and manual); baseline correction (state whether applied, and specify time window if applicable); rejection thresholds ($\pm$ µV); percentage and criteria of rejected trials (e.g., trials > ±100 µV and incorrect responses); length of clean EEG retained; software/toolbox employed (e.g., EEGLAB and BrainVision).
Feature Extraction	ERP components analysed (latency windows, channels of interest); frequency band definitions (δ, θ, α, β, γ); connectivity metrics (coherence, mutual information, Granger causality); complexity or entropy measures.
Analysis and Statistics	Type of analysis (group comparison, correlation, classification); statistical tests and corrections (e.g., ANOVA and FDR); ML model details (algorithm, validation strategy, performance metrics).
Reporting and Quality	Sample size and demographics; giftedness definition/identification criteria; data availability statement; preprocessing reproducibility (e.g., shared code or repository); ethical approval reference.

Quantitative synthesis across studies.

To complement the narrative synthesis above, Table 3 summarises the main quantitative neurophysiological results reported in the 14 included studies, ordered chronologically.

Table 3. Quantitative neurophysiological results in EEG studies on gifted children (chronological order).

Study	Year	Main EEG Feature	Quantitative Result
Alexander et al. [13]	1996	Alpha power	Group effect: $F = 37.9$, $p < 0.001$. Right Hemisphere: $F = 44.7$, $p < 0.001$.
Jin et al. (hyp. gen.) [25]	2006	A-CMI	Group effect: A-CMI: $F(1, 1728) = 13.63$, $p < 0.0005$.
Zhang et al. [30]	2006	P600; N370; LPC	P600: $F = 10.56$, $p < 0.01$. N370: $F = 10.52$, $p < 0.01$. LPC: $F = 13.71$, $p < 0.001$.
Liu et al. [32]	2007	MMN; LDN; P3a	MMN: -3.79 ± 1.70 vs. -3.25 ± 1.48 ($p < 0.005$). LDN: -3.96 ± 1.77 vs. -3.62 ± 1.50 ($p < 0.03$). LDN lat.: 480 vs. 508 ms ($p < 0.005$).
Jin et al. (ROCF) [26]	2007	Neural complexity	Complexity: $F = 10.79$, $p < 0.001$. Recall: 21.6 ± 5.9 vs. 18.4 ± 7.4 ($p = 0.047$).
Duan et al. (1-back) [31]	2009	P3; RT	P3 latency: $F = 4.32$, $p = 0.049$. RT: 561 ± 147 ms vs. 713 ± 161 ms ($p = 0.019$). Accuracy: 0.86 vs. 0.81.
Duan et al. (2-back) [29]	2009	LPC	Accuracy: 0.79 ± 0.10 vs. 0.69 ± 0.12; 0.85 ± 0.09 vs. 0.76 ± 0.16 ($p < 0.05$). LPC: $p < 0.01$.
Duan et al. (Go/NoGo) [23]	2009	NoGo-P3; errors	NoGo-P3: 377 ± 35 vs. 423 ± 74 ms ($p < 0.05$). Omission: 0.20% vs. 1.47%. Commission: 5.63% vs. 10.87%.
Duan & Shi (switching) [24]	2014	P300; RT	RT: 557 vs. 695 ms; 782 vs. 910 ms ($p = 0.008$). P300 lat.: 487 vs. 436 ms ($p = 0.02$).
Ghali et al. [21]	2019	ML accuracy	Accuracy: 65–71% (best 70.63%). Balanced: 76.88%.
Benharrath et al. (N400) [22]	2020	N400	Greater N400 in gifted (no numerical values). ISA usable with 10–12 trials.
Benharrath et al. [27]	2020	P300; features	Optimal feature subset: RMS, VAR, RANGE, 4th MOM, IQR ($J = 1.99$).
Wei et al. [15]	2020	GC; path length	Causal density: 0.83 ± 0.56 vs. 0.75 ± 0.46. Path length: θ 0.66 ± 0.12; γ 1.55 ± 0.35 ($p < 0.001$). RT: 168 vs. 231 ms. Accuracy: 79.8% vs. 63.0%.
Riccioni et al. [28]	2021	MMN; P300	MMN: 6.39 vs. 6.37 µV ($p = 0.99$); vs. HFA 4.45 µV ($p = 0.001$). Correlation: $r = 0.53$, $p = 0.035$.

Methodological evolution in EEG–giftedness studies.

Figure 3 provides a visual overview of how EEG methods applied to gifted children have evolved from early low-density resting-state recordings to more recent connectivity analyses and portable EEG/ML approaches.

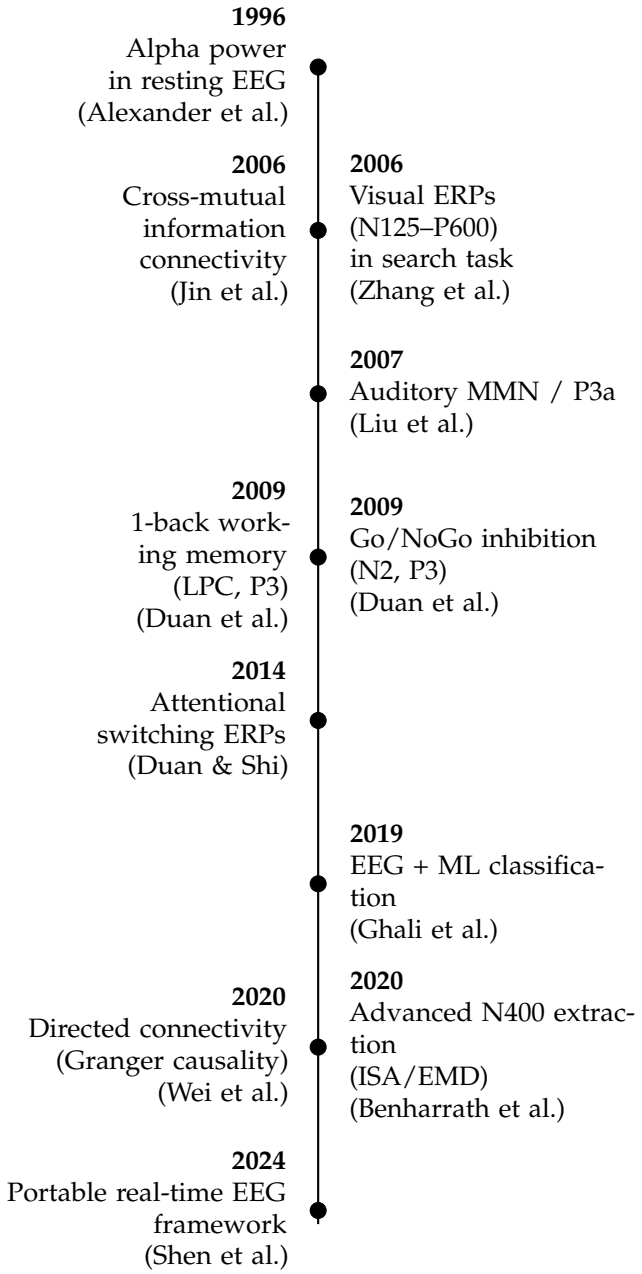


Figure 3. Timeline of methodological evolution in EEG studies on gifted children (1996–2024).

4. Discussion

This scoping review highlights how the use of EEG technologies has enabled the identification of unique neurophysiological patterns in gifted children. These findings emphasize their ability to use neural resources efficiently, which translates into significant differences in brainwave activation, event-related responses, and neural connectivity. In particular, enhanced synchronisation in frontoparietal networks and increased activity in θ, α, and γ bands reflect a form of brain optimisation that underlies higher cognitive performance. However, these interpretations should be approached with caution since they are derived from a relatively small number of studies and modest sample sizes, which limits their

generalizability. The trends observed should therefore be considered preliminary rather than conclusive.

The results support the neural efficiency theory, which posits that more efficient brains can perform complex tasks with lower energy expenditure. In the case of gifted children, the increased θ band power observed during working memory and deductive reasoning tasks aligns with their ability to integrate information and carry out advanced cognitive processes quickly and accurately. Likewise, elevated γ activity, associated with sensory integration and logical reasoning, reinforces the notion that these exceptional abilities are supported by specific brain activation patterns. Nonetheless, the existing evidence remains heterogeneous across studies in terms of paradigm, age group, and analysis method, underscoring the need for replication in larger, multicentre samples before definitive neurophysiological conclusions can be drawn.

Enhanced event-related potential responses such as P300, N400, and MMN also demonstrate more efficient processing of relevant stimuli and a greater capacity to inhibit irrelevant information. These findings highlight differences in neural processing and open the door to technological and educational applications that leverage these characteristics. However, this review also reveals several methodological limitations. The disparity in study approaches, such as varying EEG configurations (number of channels, sampling rates) and different analytical techniques (ERP, feature analysis, mutual information), hinders a direct comparison of the results. Notably, many studies focused on the analysis of the P300 potential, which emerges as a recurrent marker in giftedness research. Still, the consistency of P300 findings across several independent studies should not be misinterpreted as evidence of a biomarker; rather, it indicates a promising direction that requires harmonised task designs and unified preprocessing criteria to verify its robustness.

A critical aspect is the variability in EEG preprocessing pipelines. Steps such as artefact rejection, ocular correction, filtering, baseline adjustment, or feature extraction are applied differently across studies, directly impacting comparability and reproducibility. The absence of a unified standard makes it difficult to determine whether observed differences are due to neurophysiological variability in the participants or to technical differences in signal processing. Establishing a gold standard for EEG pipelines in giftedness research, covering acquisition, preprocessing, feature extraction, and analysis, would allow the field to move toward more consistent and transparent methodologies. This would strengthen reliability and enable replication across independent cohorts. In this sense, future works should explicitly report methodological parameters such as montage, sampling rate, reference scheme, filter settings, artefact thresholds, percentage of rejected trials, and the specific software or toolboxes used. This level of transparency would substantially improve reproducibility and facilitate meta-analytic integration.

In this context, the use of machine learning algorithms in EEG analysis emerges as a promising direction. Once signals are preprocessed and transformed into robust features, ML models such as decision trees, boosting techniques, or neural networks could identify subtle patterns linked to giftedness. These tools may improve the accuracy of identification and offer an innovative approach to integrating neuroscience into educational settings. Furthermore, the development of portable EEG devices with real-time preprocessing and embedded classification capabilities could facilitate accessible evaluations, enabling the continuous monitoring of cognitive and emotional performance. However, the current literature in this area is still exploratory. Reported classification accuracies should be interpreted as proof-of-concept findings rather than as validated predictive systems. Future work should emphasize external validation, cross-dataset testing, and interpretability to ensure robust and ethically responsible applications.

Despite these advances, this review underscores several limitations in current studies. The heterogeneity of EEG configurations and analysis methods complicates direct comparison of findings, while the small sample sizes limit the generalisation of results. Most investigations also adopt a cross-sectional approach, analysing data at a single point in time, which prevents the evaluation of developmental trajectories in neurophysiological differences. To overcome these constraints, longitudinal and cross-institutional designs are encouraged, allowing researchers to capture developmental changes in neural efficiency and connectivity across schooling years.

In addition, it is important to note that the selection of primary school children, typically between 5 and 13 years of age, is grounded in both developmental and educational considerations. This age range encompasses a critical window in which foundational cognitive functions, such as attention, working memory, and executive control, undergo rapid maturation and are highly sensitive to individual differences. It is during this stage that early manifestations of high intellectual potential can be most clearly observed and meaningfully differentiated from typical development. Moreover, this period coincides with the early years of formal education, where timely identification of giftedness can have a significant impact on academic trajectories. Focusing on this population allows researchers to investigate the neurophysiological correlates of giftedness at a stage when cognitive abilities are still developing, thereby offering insights into the early neural markers of high ability and informing the design of targeted educational interventions. This developmental perspective also highlights the importance of designing EEG paradigms that are non-invasive, age-appropriate, and suitable for real educational environments rather than strictly laboratory settings.

As shown in Figure 4, the lack of consistency in how acquisition, preprocessing, and feature extraction are reported highlights the need for a more transparent and standardised pipeline across studies. Moving forward, community-driven efforts to establish open EEG repositories and consensus reporting standards could greatly enhance methodological comparability and accelerate cumulative progress in this area.

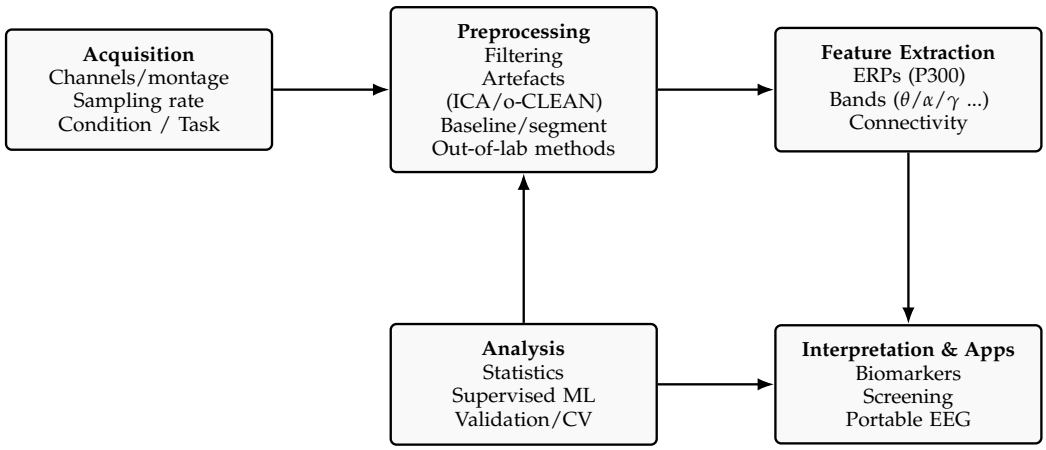


Figure 4. EEG pipeline synthesised from the reviewed studies.

From these limitations, future lines of research can be outlined as follows:

- Standardize EEG acquisition and preprocessing pipelines to facilitate comparability between studies, ensuring that steps such as filtering, artefact rejection, and feature extraction follow transparent and replicable criteria. To enhance reproducibility and comparability in EEG studies on giftedness, it is proposed to standardize signal processing pipelines by defining specific parameters for each stage. During acquisition, a minimum of 32 electrodes following the 10–20 system and a sampling rate of at least 256 Hz are recommended to ensure sufficient spatial and temporal resolution.

In the preprocessing stage, band-pass filtering between 0.1 and 40 Hz, ocular and muscular artefact correction via ICA, and rejection of epochs exceeding ±100 µV should be applied. Feature extraction should focus on ERP components such as P300 and N400, as well as spectral power in α, θ, and γ bands. For the analysis stage, it is advisable to combine traditional statistical methods with machine learning classifiers (e.g., SVM and random forest) trained on validated cognitive metrics. The adoption of such standardised pipelines would facilitate methodological consistency and support the development of robust, scalable tools for the objective identification and characterisation of giftedness. These parameters should be regarded as guiding principles rather than strict requirements, adaptable to diverse experimental aims and educational contexts.

- Investigate the evolution of neural connectivity and brain synchronisation throughout childhood development to gain a deeper understanding of neurophysiological changes in gifted children. Longitudinal studies could reveal whether neural efficiency patterns reflect stable traits or developmental adaptations shaped by learning environments.
- Develop more accessible and accurate portable EEG systems with embedded preprocessing algorithms to enable real-time assessments in educational and clinical settings. Such systems could significantly increase ecological validity and make EEG-based research feasible in schools, while maintaining adequate data quality.
- Integrate artificial intelligence into EEG pipelines to optimize feature selection and classification accuracy while reducing data processing time. A key priority should be ensuring model interpretability and ethical transparency so that these algorithms can provide meaningful insight rather than opaque predictions.
- Explore the use of EEG as a complementary tool in the identification of giftedness, given that traditional questionnaires and diagnostic tests present limitations in terms of time and precision. EEG could serve as a preliminary screening tool, helping to identify gifted children more objectively and at an earlier stage, thereby optimizing educational assessment processes. Nonetheless, EEG-based approaches should complement, never replace, multidimensional psychometric and behavioural evaluations, ensuring balanced and fair identification.
- Further analysis of γ synchronisation in frontoparietal regions during complex tasks to test neural efficiency hypothesis in gifted children. It would also be valuable to compare task-dependent and resting-state γ dynamics to better understand their cognitive relevance.
- Design of personalised pedagogical interventions grounded in real-time neurophysiological data. These interventions should aim to support adaptive learning rather than label or segregate students, emphasizing ethical and inclusive applications of neurotechnology.
- Investigate potential associations between EEG features and standardised measures of intelligence as a research avenue, without implying direct estimation. Future work could examine whether patterns of neural efficiency or connectivity correlate with psychometric performance, providing a theoretical framework for understanding cognitive potential rather than a diagnostic application.
- Translate EEG findings into actionable pedagogical applications. Future studies should investigate how indicators such as cognitive load, attentional engagement or neural efficiency can guide instructional design and curriculum adaptation [37]. EEG could help to detect underchallenge or overstimulation, adjust task difficulty, and evaluate the impact of enriched programs or physical-activity interventions on learning. This line of work would bridge neurophysiological evidence with classroom practice, supporting data-informed and adaptive educational strategies.

Overall, this review reinforces the role of EEG as a crucial tool for studying giftedness. Advances in biomedical engineering and applied neuroscience, especially through the development of standardised preprocessing pipelines and the incorporation of artificial intelligence, have the potential to transform how this population is identified and supported, promoting a more inclusive and effective approach. In contrast to previous systematic reviews, such as that by Kuznetsova et al. [19], which focused on synthesizing cognitive and physiological findings, the present work emphasises the engineering and methodological dimensions of EEG research. Both perspectives are complementary, suggesting that progress in the field requires not only identifying relevant neural markers but also ensuring that the pipelines used to detect them are transparent, standardised, and reproducible. By grounding future EEG–giftedness research in rigorous methodology and ethical responsibility, the field can move toward reproducible, interpretable, and socially beneficial applications of neurotechnology in education.

5. Conclusions

This scoping review highlights the usefulness of electroencephalography as a key tool for understanding the neurophysiological foundations of giftedness in children. Throughout the analysis, distinctive patterns were identified in neural connectivity, brainwave synchronisation, and event-related responses, which are indicative of greater neural efficiency in this population. These findings not only support theories such as the neural efficiency hypothesis but also emphasize the relevance of using advanced technologies to explore brain function in gifted children.

Furthermore, the emerging role of machine learning algorithms and portable EEG devices suggests potential opportunities for early and more personalised identification approaches. These technological developments could be relevant in educational and clinical settings, contributing to more efficient evaluation processes. However, despite this progress, there is still no gold standard for the identification of gifted children through EEG, which limits the integration of these methods into applied contexts. Establishing a validated and widely accepted protocol would help complement traditional assessments, which often rely on subjective or time-consuming procedures.

A crucial step toward this objective is the development of standardised EEG pipelines. Differences across studies in acquisition parameters, preprocessing procedures (e.g., filtering, artefact rejection, and baseline correction), and feature extraction strategies currently hinder comparability and reproducibility. A methodological consensus would not only increase the robustness of findings but also facilitate the integration of EEG into interdisciplinary research frameworks. By creating a transparent and replicable sequence of acquisition–preprocessing–analysis, research on giftedness could progress toward more consistent clinical and educational applications.

At the same time, the literature shows important limitations, including methodological heterogeneity, small sample sizes and a scarcity of longitudinal studies. These constraints limit the generalizability of current findings and highlight the need for more standardised, collaborative, and long-term research efforts. Future work should also draw on advances from related EEG domains, including the development of subject-independent machine learning models, multimodal approaches combining EEG with behavioural or physiological data, and deep feature extraction methods capable of capturing complex neural patterns with minimal manual preprocessing. Likewise, the rapid growth of portable and classroom-ready EEG systems (e.g., Emotiv Inc., San Francisco, CA, USA; InteraXon Inc., Toronto, ON, Canada; Bitbrain Technologies, Zaragoza, Spain) opens the possibility of conducting ecologically valid, real-time assessments in school environments, an area that remains largely unexplored in giftedness research.

Even with these challenges, combining EEG recordings with advanced analytical techniques represents a promising avenue for developing supportive neurophysiological screening tools. While not intended as diagnostic instruments, such tools could assist and streamline assessment processes by identifying potential biomarkers of giftedness and facilitating earlier and more accurate differentiation from other cognitive profiles.

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Abbreviations

The following abbreviations are used in this manuscript:

EEG	Electroencephalography
ERP	Event-Related Potentials
ICA	Independent Component Analysis
EMD	Empirical Mode Decomposition
PCA	Principal Component Analysis
AI	Artificial Intelligence
ML	Machine Learning
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses

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