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EEG-Based Intent Classification for BCI User Interface Control

Background and Challenges

Brain–Computer Interfaces (BCIs) enable users to control software or devices via EEG signals, offering alternative interaction methods for individuals with motor impairments and novel UI paradigms for healthy users. For example, BCIs have been explored to execute discrete interface actions like showing/hiding panels or switching modes without muscle input. However, EEG intent classification is non-trivial: the signals are extremely weak, noisy, and non-stationary [1]. Noise from eye blinks, muscle activity, and environmental interference can obscure neural patterns, and each user's brain signals differ and even the same user's signals drift over sessions [2]. These factors complicate real-time classification and necessitate careful signal processing and personalization. Active EEG-based BCIs also typically have lower bandwidth and speed than conventional inputs – for instance, the fastest reported "brain switch" (a one-command asynchronous BCI) still requires ~1.5 seconds on average to reliably activate a command [3], much slower than a mouse click. Despite these challenges, recent research (especially in the past 5 years) has shown that *simple EEG features* combined with *classical machine learning* can achieve robust intent detection, particularly in low-training-data scenarios, by emphasizing good signal preprocessing and user-specific modeling.

Signal Preprocessing and Feature Extraction

Effective EEG preprocessing is a **prerequisite** for reliable classification. Nearly all pipelines begin with artifact reduction and quality enhancement steps. Raw EEG is typically band-pass filtered (e.g. 0.5–40 Hz) to remove slow drifts and high-frequency noise, and notch-filtered (50/60 Hz) to suppress power-line interference. Beyond filtering, methods to remove physiological artifacts are crucial: electrooculogram (EOG) and electromyogram (EMG) artifacts can be mitigated via techniques like Independent Component Analysis (ICA) or Principal Component Analysis (PCA) that isolate and subtract noise components [4]. Some pipelines automatically detect and reject segments with excessive noise (e.g. based on amplitude thresholds or probability maps of artifacts) to prevent garbage data from contaminating the classifier. These steps **improve signal quality without losing important information** [4] and have become standard in modern BCI preprocessing.

After cleaning, features are extracted that capture the user's *intent-relevant EEG patterns* in a compact form. Unlike deep learning approaches that learn abstract features, classical BCI systems deliberately compute physiologically interpretable features. **Band power features** are among the most common: EEG is divided into canonical frequency bands (delta, theta, alpha, beta, gamma), and the power (energy) in each band over a given time window is computed (often via FFT or Welch's method). These band powers can reveal task-specific EEG changes. For example, motor-imagery (MI) tasks (the user imagining left-hand vs right-hand movement, etc.) cause event-related desynchronization (ERD) in the mu (8–13 Hz) and beta (~14–30 Hz) rhythms over the contralateral sensorimotor cortex. By measuring band power in these bands at left vs right hemisphere electrodes, one can discriminate different MI commands [5]. In fact, BCIs for *motor intent* often rely on such features – Pfurtscheller's early work showed that changes in mu/beta band power could enable 1D cursor control via imagined hand movements, and later systems generalized this to 2D control by mapping left-vs-right and foot-vs-hand imagery to X/Y cursor movements. Steady-state visually evoked potential (SSVEP) BCIs (commonly used for menu selection or wheelchair navigation) also use band-power: the user focuses on a flickering UI element, and the EEG power at the flicker frequency indicates the selection [6]. **Band power ratios** (relative power) are another simple feature that can normalize individual differences – e.g. the ratio of theta to beta power is a known index of drowsiness or workload, and has been used to gauge user state in adaptive interfaces [7]. Similarly, **hemispheric asymmetry** features capture differences between the EEG power over the left and right hemispheres. One application is *frontal alpha asymmetry (FAA)*, defined as the difference in alpha-band power between right and left frontal regions; FAA has been used as a control signal in affective BCI interfaces [8]. For instance, Krogmeier *et al.* (2022) mapped FAA in real time to a continuous UI parameter, allowing users to modulate a game character's attributes via asymmetric alpha activity [8]. In a classification context, asymmetry measures (e.g. an asymmetry index per band) can be input features alongside raw band powers – a recent endogenous BCI study, for example, used spectral band powers *and* inter-hemispheric asymmetry ratios together in a traditional classifier framework to improve discrimination of mental states [8] [9].

Other handcrafted features are also used depending on the paradigm: time-domain statistics (e.g. signal amplitude means or variance in specific time windows), temporal patterns like event-related potential (ERP) peaks (for instance, the P300 wave ~300 ms after a target stimulus in an oddball task), and time-frequency or spatial features. Notably, **Common Spatial Patterns (CSP)** is a widely-used spatial filtering method in motor-imagery BCIs: CSP finds a linear combination of electrodes that maximally separates two conditions by their band-power, effectively enhancing the ERD contrast [10]. CSP-transformed variance features paired with a simple linear classifier have historically won many BCI competitions for MI. Simpler spatial approaches include focusing on only a few key channels (e.g. C3/C4 for motor cortex) or computing differential features (like left minus right power, which is a basic asymmetry measure). Regardless of the specific features, the goal is to reduce the high-dimensional EEG (dozens of channels, thousands of time points) to a manageable feature vector that *distills the intent-related signal*. Typical feature vector lengths range from <10 features (when using just a few band powers or ratios) up to a few hundred (if using multi-band CSPs or wavelet coefficients, etc.). Feature selection techniques are often applied to avoid overfitting: for example, Degirmenci *et al.* (2024) computed a large set of features across time, frequency, time-frequency, and nonlinear domains, then applied a statistical significance test to retain only the most discriminative features. This pruning significantly improved their motor-imagery classification accuracy while using fewer features [11].

Classification Algorithms for EEG Intent Detection

Once features are extracted, a **classifier** is trained to map them to user intents (commands). In keeping with the focus on *classical* machine learning, researchers have favored well-established, relatively simple classifiers that perform reliably on small datasets. **Linear classifiers** are especially popular due to their low complexity and interpretability. **Linear Discriminant Analysis (LDA)** and its regularized variants have been a staple in BCI – for instance, many P300 speller systems use stepwise LDA to detect the P300 component for character selection, and early motor BCIs often employed LDA for two-class motor imagery. **Logistic Regression (LR)** is another linear method used for single-trial EEG classification [12]; like LDA, it produces a linear decision boundary in feature space, but offers probabilistic outputs and can be regularized (e.g. L1 or L2 penalty) to combat overfitting. LR was proposed in some early BCI work as a robust alternative to LDA [12] and continues to be used in recent studies (e.g. Chen *et al.* 2022 applied a weighted logistic regression for motor imagery classification with success). **Support Vector Machines (SVMs)** are frequently applied as well, especially for binary intent detection. SVMs with a linear or RBF kernel can handle high-dimensional feature inputs and have strong regularization properties, which is valuable given the limited EEG sample sizes. In practice, LDA, LR, and linear SVM often yield comparable results on band-power features, so the choice may come down to tuning and preference [13]. Table 1 provides a comparison of representative EEG intent classification approaches, illustrating typical features, classifiers, dataset sizes, and performance outcomes.

Table 1. Example EEG-Based BCI intent classification methods (recent studies unless noted). Performance is classification accuracy unless specified.

Study (Year)	**BCI Task / Dataset**	**Features Used**	**Classifier(s)**	**Dataset Size**	**Performance**
Mandel *et al.* (2009) [14]	SSVEP-based wheelchair control (4 commands)	Band-power at stimulus frequencies (SSVEP)	Linear classifier (LDA)	n=4 subjects (est.), multiple trials under stress vs calm	~93.6% accuracy during wheelchair movement [14] (minimal performance drop under stress)
Degirmenci *et al.* (2024) [15] [16]	Motor imagery (BCI Comp. IV 2a: 4-class MI)	Time, frequency, time-freq, nonlinear features; feature selection for significance	9 classifiers tested: LR, SVM, kNN, Decision Tree, Naive Bayes, etc; best = Ensemble (Random Forest)	9 subjects, 288 trials each (4 classes) [17]	~63% max. for binary MI (vs 50% chance), ~47% for 4-class (vs 25%) [16]. Ensemble methods performed best.
Das *et al.* (2025) [18] [19]	Motor imagery & movement (PhysioNet EEG-MMIDB open dataset)	Band-pass & wavelet filtered signals; CSP/Riemannian covariance features; PCA/t-SNE for dimensionality reduction [20] [21]	Traditional ML: kNN, SVM, LR, Random Forest, Naive Bayes; Deep CNN and LSTM; Hybrid CNN-LSTM	109 healthy subjects, 64-ch EEG (multiple motor tasks) [19]	Best classical: Random Forest 91% [22]. CNN ~88%, LSTM ~16% (underfit), Hybrid CNN+LSTM ~96% [18]. Hybrid deep model outperformed others on this large dataset.
Eder *et al.* (2024) [23] [24]	Multiple paradigms (MI, P300, SSVEP) – 12 open datasets (MOABB benchmark)	Filter-bank covariance matrices (spatial features); raw EEG for CNN	Riemannian classifier (minimum distance to mean in covariance space) and LDA vs. CNNs (EEGNet, Shallow/Deep ConvNets)	>150 subjects across datasets; evaluated within-session, cross-session, cross-subject [25]	No **significant** difference in accuracy between CNNs and the best Riemannian+LDA approach in any condition [13]. Classical methods matched deep nets across tasks when tuned properly.

As shown above, classical machine learning methods remain highly competitive for EEG intent classification. Simpler linear or ensemble classifiers often perform on par with deep networks in BCI tasks when using well-chosen features, especially for small training sets [13]. For example, Degirmenci *et al.* achieved ~63% on binary motor imagery (far above chance level) using only hand-crafted features and traditional classifiers [16], and in their tests an ensemble (random forest) slightly outperformed SVMs and neural nets. Similarly, in the open PhysioNet motor imagery dataset, a tuned random forest attained 91% accuracy, surpassing a basic CNN on the same data [18]. On the other hand, when abundant data are available, hybrid deep architectures can excel (the CNN+LSTM in Das *et al.* [26] reached 96% on PhysioNet, suggesting that learning both spatial filters and temporal dynamics can boost performance given enough training samples). These results underscore an important point: with limited data, simpler models with domain-specific features tend to shine, whereas deep learning's advantage emerges mainly with larger datasets or the ability to pre-train/transfer knowledge. A 2024 benchmark study by Eder *et al.* reinforces this – it systematically compared modern CNNs (EEGNet and variants) against covariance-based Riemannian classifiers on dozens of subjects' data for three BCI paradigms, and found **no significant performance difference** between deep and classical approaches [13]. This parity held true not only for within-session classification but also in more challenging cross-session and cross-subject scenarios [24]. In short, classical ML remains a strong baseline (and often the method of choice) for intent recognition in BCIs, due to its robustness with small data and easier interpretability.

Beyond classifier choice, **personalization** is critical. EEG BCIs almost always use *subject-specific models*, meaning the system is calibrated on each individual. This is necessary because of large inter-subject variability – differences in skull anatomy, electrode contact, and idiosyncratic brain patterns mean a model trained on one person's EEG will perform poorly on another's without adaptation [2]. Typically, a calibration session is conducted for each user, where they perform the mental commands in a guided manner to provide labeled training data. The entire signal processing pipeline (filters, feature selection, classifier parameters) is tuned to this personal data [27] [28]. Research has documented that obtaining enough calibration data is a bottleneck: many public EEG datasets have only a few dozen trials per class for each subject [29] [30]. Indeed, one rule of thumb suggests at least ~40 trials per class are needed to exceed 70% accuracy for a new user, below which "BCI illiteracy" becomes likely [30]. Long calibration sessions, however, can exhaust users and are impractical for real-world use [31], so a major goal in recent BCI research is reducing the required training or making models generalize better. Two strategies have emerged: (1) **Transfer learning** – using data from other subjects or sessions to inform the model for a new user – and (2) **Adaptive learning** – updating the model on-the-fly using unlabeled or minimally labeled data from the current session.

Transfer learning in BCIs can involve *cross-subject* or *cross-session* approaches. Cross-subject transfer might use a pool of existing subjects' data to pre-train a classifier or to construct subject-invariant feature representations, then fine-tune to the new individual. Cross-session (or longitudinal) transfer addresses session-to-session signal drift for the same subject: for example, **baseline normalization** is a simple but effective technique where each session begins with a brief rest period to record baseline EEG, and features are then referenced to this baseline (e.g. by subtracting the mean alpha power at rest from subsequent active trials). This can compensate for global shifts in signal amplitude or impedance changes. More sophisticated is the Riemannian alignment method by Zanini *et al.* (2018): they recorded a few minutes of resting EEG at the start of each session and used it to compute a reference covariance matrix for that session. By whitening each session's data with its rest covariance (mapping it to a common reference), they greatly reduced inter-session variability [32]. Such alignment allowed a classifier trained on past sessions to maintain accuracy on a new session with minimal or no new training. Other transfer learning methods re-weight or select training data from a large pool based on similarity to the target user, or train neural networks that have some subject-invariant layers and some subject-specific layers [33] [34]. Overall, transfer learning has shown promise to shorten calibration time by *leveraging existing labeled data* [35] [36]. For instance, one approach is to use a large ensemble of models from many subjects and then pick or adapt the ones most suitable for the new subject's initial data [33].

In parallel, **adaptive online learning** can handle *session drift* during use. Semi-supervised and unsupervised adaptation techniques continuously update the classifier using the stream of incoming EEG. For example, one can use the classifier's confidence scores to slowly adapt decision boundaries (assuming that high-confidence outputs are likely correct labels) [37]. Researchers have combined transfer and semi-supervised learning: e.g. start with a model transferred from prior data, then adapt it with unlabeled data from the new session to fine-tune to that session's idiosyncrasies [38] [39]. Such hybrid approaches can reduce the calibration burden while maintaining personalization. It's worth noting that despite these advances, **subject-specific calibration is still often necessary** for reliable performance – completely calibration-free BCIs remain an open challenge in the field, especially for subtle intent signals. Nevertheless, recent competition-winning algorithms (e.g. based on Riemannian geometry or few-shot meta-learning) are making progress toward minimal calibration BCIs by better accounting for inter-subject differences.

Figure 1: Typical EEG BCI workflow consisting of a calibration (training) phase and an online testing phase [27] [28] *. During calibration, the user provides labeled EEG examples of each intent (e.g. "hide panel" vs "show panel"), which are preprocessed into features and used to train a subject-specific classifier. During online use, the EEG is processed in the same way and the trained model predicts the user's intent from each new feature vector, triggering the corresponding UI command. Continuous feedback (e.g. the panel actually hiding or showing) allows the user to see the result and potentially modulate their strategy.*

Another practical concern is **artifact management at runtime**. Even after offline cleaning, unexpected artifacts can occur during operation (for example, the user may cough or shift in their seat, causing EMG bursts). Robust BCI systems include artifact rejection mechanisms in real-time – e.g. pausing classification if signal quality metrics drop or using additional sensors (like an EMG on the jaw) to detect and ignore movement artifacts. Notably, a recent study examined how aggressive artifact removal impacts classifier performance, and somewhat surprisingly found that in many cases, eliminating all artifacts didn't significantly improve SVM decoding accuracy [40] . This implies that mild artifacts (or user's compensatory strategies) sometimes do not ruin the classification, and overly heavy-handed filtering can even remove informative signal. The takeaway is that a balanced approach is needed: filter and reject only what's necessary to maintain signal quality, and rely on the classifier's robustness and any ensemble averaging to handle residual noise. Some modern pipelines use automated tools (e.g. *Autoreject*, *FASTER*, or *MARA* in EEGLAB) to auto-clean EEG and flag bad trials. For instance, there are pipelines that perform **state-based artifact suppression**, where a recurrent model imputes or removes segments classified as artifact without discarding the whole trial [41] . Regardless of method, incorporating artifact handling is essential for any real BCI used in practical settings, as it maintains a low false positive rate and ensures the system responds only to genuine user intents.

Comparisons to Deep Learning Approaches

In recent years, deep learning has of course made inroads into EEG classification. Models like EEGNet (a compact CNN architecture for BCI signals) and various RNNs or Transformers have been proposed to automatically learn features from raw EEG. These approaches have shown impressive results in some cases (especially with big EEG data), but the **consensus in 2025** is that deep models have not categorically displaced classical methods for BCI control tasks. One reason is the *limited size of typical EEG datasets*, which makes training large neural networks difficult. Deep networks have high capacity and can overfit when only a few dozen trials per subject are available [42] . Classical features like band power, on the other hand, embed prior knowledge (e.g. which frequency ranges matter) and thus require the classifier to learn only a few parameters, which is more data-efficient. As a result, studies often find that with the same small dataset, a tuned simpler model will match or outperform a deep net. For example, in the motor imagery classification study by Das *et al.* (2025), the best traditional classifier (Random Forest) scored 91% accuracy on the PhysioNet EEG imagery data, whereas a 4-layer CNN reached about 88% [18] . Only by combining CNN and LSTM (with significantly more trainable parameters and by leveraging the larger size of that dataset) did the deep approach exceed 96% [43] , a gain accompanied by much higher computational cost. Similarly, EEGNet (a CNN) was shown to perform about on par with filter-bank CSP + LDA in many BCI tasks; Lawhern *et al.* (2018) reported EEGNet achieved ~%67 on a 2-class MI task versus ~65% for FBCSP-LDA, a difference not statistically significant. The comprehensive 2024 benchmark by Eder *et al.* concluded that *"the choice between CNNs and Riemannian [classifier] methods may not heavily impact decoding performance"* for standard BCI paradigms, as they found no significant difference in accuracy in multiple conditions [13]. This finding gives BCI developers flexibility to choose algorithms based on practical factors (ease of implementation, speed, interpretability) rather than worrying about a large performance trade-off [44].

That said, deep learning offers some advantages: deep models can learn end-to-end mappings, potentially obviating the need for manual feature extraction. They can also integrate feature extraction with classification in one optimized pipeline (e.g. learning spatial filters akin to CSP as the first conv layer). In cases where large pooled datasets are available or when doing off-line analysis on big data (like thousands of EEG hours), deep networks (especially with data augmentation or transfer learning) have exceeded classical approaches. We see this in EEG-based emotion recognition and sleep staging domains where deep architectures dominate. For intent classification BCIs, there are also hybrid approaches that incorporate deep learning in a limited way – for instance, using an autoencoder or GAN to **augment data** with synthetic EEG samples [20] [45]. Das *et al.* (2025) did this by generating artificial EEG trials via a GAN to enlarge training data, then training their hybrid CNN-LSTM, which likely contributed to its high accuracy [46] [47]. Another trend is using pre-trained deep models (perhaps trained on a large unrelated EEG database) and fine-tuning them on the small target BCI dataset – analogous to transfer learning in image recognition. This can give deep learning a better starting point, combining the benefits of big-data training with small-data adaptation [48]. Nonetheless, these techniques are still in experimental stages for BCIs, and the *added complexity must justify itself* with clear gains. In contexts like real-time UI control for healthy users, simplicity and reliability are paramount; thus many researchers stick to simpler pipelines that are easier to calibrate and explain. As Shishkin (2022) noted, non-invasive BCIs for healthy users have such stringent competition (keyboard, mouse, voice, etc.) that only highly reliable and fast solutions are viable [49] [3] – a slightly higher accuracy from a complex deep net might not be worth the latency or development overhead if a simpler method already achieves the needed performance.

Open Datasets and Tools

To drive progress, the BCI field has embraced open science, resulting in many accessible **EEG datasets** and benchmarking tools. For example, the **PhysioNet EEG Motor Movement/Imagery Dataset** (EEG-MMIDB) used by Das *et al.* is a public repository of EEG from 109 healthy adults performing 14 motor tasks (imagine or execute hand/foot movements). It provides over 1,500 one- to two-minute EEG recordings and is freely available on PhysioNet [19] [50]. Likewise, the **BCI Competition** series and the related **BNCI Horizon 2020** initiative have released numerous datasets covering common BCI paradigms. One prominently used set is **BCI Competition IV Dataset 2a**, which contains 4-class motor imagery EEG from 9 subjects (used in Degirmenci et al. 2024) [17]. Other open datasets include those for P300 spellers (e.g. BNCI 2014-009), SSVEP-based BCIs (e.g. BNCI 2014-008), and various hybrid or cognitive BCI tasks [25]. These datasets typically involve healthy adult participants and are accompanied by papers describing the experimental setup, making them valuable for method development and fair comparisons. Researchers are encouraged to evaluate new classifiers on these standard datasets to benchmark against prior results – for instance, a new intent classification algorithm might be tested on BCI Competition data to show it outperforms the LDA+CSP baseline.

In terms of software, there are now comprehensive **toolkits** that support BCI algorithm research. A notable example is **MOABB (Mother of All BCI Benchmarks)** [51] – an open-source Python library that aggregates dozens of EEG datasets and provides a consistent pipeline to evaluate algorithms on them. MOABB was used by Eder *et al.* (2024) to compare CNNs and Riemannian classifiers across tasks, and it includes implementations of many classical methods (LDA, SVM, logistic regression) as well as deep models like

EEGNet [52] [53]. By using MOABB, researchers can easily conduct statistically rigorous comparisons with unified preprocessing, which helps identify if an observed performance gain is truly due to a new algorithm or just due to different data handling. The **code** for Eder et al.'s benchmark was released publicly [54], as was the code for EEGNet and other deep models (e.g. the *EEGModels* GitHub repository by Lawhern *et al.*) [55]. Such resources lower the barrier to entry – one can take an off-the-shelf implementation of, say, a Riemannian classifier or an EEGNet, and immediately test it on a known dataset as a baseline. There are also domain-specific tools like **PyRiemann** (for covariance-based classification) [56] and popular general EEG analysis platforms (EEGLAB, MNE-Python, BCILAB) that incorporate machine learning for BCI. For online BCI development and UI integration, frameworks like **BCI2000** and **OpenViBE** allow developers to plug in custom classifiers (e.g. a logistic regression model) and deploy a real-time system with a user interface. Many of the research papers also share their trained models or source code – for instance, the hybrid CNN-LSTM of Das et al. was described in detail, and while the code wasn't linked in the paper, the model architecture can be reconstructed from the publication. The trend toward open data and code means that anyone interested can replicate and build upon the latest EEG intent classification approaches, accelerating progress in the field.

Conclusion

In summary, EEG-based intent classification for BCI control of user interfaces is a mature yet active research area. Approaches emphasizing *simple, interpretable features* (like band power, ratios, and asymmetries) and *classical classifiers* (LR, SVM, LDA, etc.) have proven effective, especially when paired with rigorous artifact handling and user-specific calibration. Such methods achieve reliable accuracy for discrete UI commands (often in the 70–90% range for binary decisions in healthy users [16] [57]) while using relatively few training samples. Personalization is a cornerstone – models are tailored to each individual and even each session, through calibration data and techniques to compensate for signal non-stationarity [2]. This ensures stability over time and across users, albeit at the cost of some calibration effort. To put these classical approaches in context, they often perform on par with far more complex deep learning models for the common BCI tasks [13], reinforcing that "deep is not always necessary" – judiciously designed shallow pipelines can extract the key information the brain is conveying about the user's intent. Indeed, the simplicity of band-power features and linear classifiers can be an advantage in real-world deployment: they are fast to compute, require minimal parameter tuning, and their decisions can be interpreted (e.g. which frequency band or electrode was most influential), which is useful for debugging and for user feedback.

That said, the field is not standing still. Hybrid systems that blend the best of both worlds are emerging – for example, using a deep network to *assist* feature extraction (learning optimal spatial filters or generating synthetic data) but still employing a lightweight classifier on top. There is also growing interest in expanding beyond traditional motor or visual-evoked tasks into higher-level cognitive intents (like "interest" vs "disinterest" which might control information filtering in an interface). These higher-level intents often rely on subtle EEG correlates (e.g. frontal theta for workload or alpha asymmetry for emotional state), again lending themselves to simple feature approaches combined with personalized modeling. Comparisons with deep learning will continue, but current evidence suggests that for many BCI UI applications, a thoughtfully engineered classical approach is not only sufficient but perhaps ideal when training data are scarce. Researchers are thus continuing to refine these methods – improving artifact robustness, feature selection, and transfer learning – to inch closer to BCIs that are **fast, accurate, and require minimal user training**. Such advancements will ultimately enable practical brain-controlled user interfaces, whether it's a patient toggling an assistive device on/off with a thought or a power-user hands-free opening a virtual panel via EEG. The progress over the last five years, aided by open datasets and interdisciplinary innovation, makes it clear that combining neuroscience insights (simple, meaningful EEG features) with proven machine learning (classifiers and adaptation techniques) is a winning formula in BCI intent classification research [42] [13].

Sources: Recent literature and open benchmarks on EEG-based BCI classification, including Frontiers and Scientific Reports articles from 2020–2025 [15] [18] [13], foundational BCI research [9] [4], and open data/tool repositories [19] [53]. The table summarizes key studies to illustrate methods and results.

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