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Mapping the literature about brain-computer interface in rehabilitation: a graph-theory-based PCA framework for semantic space analysis

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Abstract

Brain-Computer Interfaces (BCIs) are increasingly used in neurorehabilitation, but the rapid expansion of scientific literature complicates the identification of clinically relevant studies. This study investigated whether expert-defined relevance within BCI rehabilitation literature emerges as a structural property of semantic networks through the integration of graph theory and Principal Component Analysis (PCA). A Lexical Network Analysis Based on Graph Theory (LENGTH) was applied to randomized controlled trials indexed in PubMed over the last decade using the query "brain computer interface" AND rehabilitation. Titles and abstracts were analyzed to construct a semantic network linking articles and lexical terms. Multiple graph-theoretical metrics were calculated and residualized against weighted degree to minimize document-size bias. PCA was subsequently applied to the residualized metrics. Forty-eight studies were included. The network showed a compact and highly interconnected structure, centered on motor and functional recovery concepts. PCA identified two principal components explaining of total variance. Relevant articles tended to occupy regions characterized by higher semantic integration and lower hierarchical influence. Although no clear categorical separation emerged, a consistent positional tendency was observed. These findings suggest that relevance may be represented as a topological property within a multidimensional semantic landscape, supporting the use of semantic-network approaches for literature screening and evidence synthesis.

Key Words: brain-computer interface; neurorehabilitation; graph theory; network analysis; principal component analysis.

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Brain-Computer Interface (BCI) is a system that receives signals from a patient's brain, integrates them and returns a specific output.[1] It is increasingly integrated into standard rehabilitation protocols by using different patient-driven therapeutic modalities.[1] By facilitating direct, bidirectional communication between the brain and external devices, BCIs engage neural pathways and induce use-dependent neuroplasticity, maximizing functional recovery.[2] Additionally, BCI training's ability to rapidly drive structural and functional brain changes, even within brief sessions, supports its role as a multimodal cognitive-motor intervention, targeting both motor and cognitive deficits in neurological injury.[3] However, efficacy remains highly variable across patients and the literature shows numerous ways of applications.[4] From a technological standpoint, different BCI systems exist with different levels of invasiveness.[5] Invasive systems, such as electrocorticography, offer superior spatiotemporal resolution, but their rehabilitative application is constrained by implantation risk.[6] Non-invasive systems therefore define the standard of care in neurorehabilitation, with electroencephalography and functional near-infrared spectroscopy representing the dominant modalities.[7] Despite limitations in spatial resolution and susceptibility to artifacts, their safety profile, portability, and cost-effectiveness establish them as the clinical gold standard.[7] From a clinical point of view, the application of BCI in rehabilitation has expanded rapidly to encompass a wide spectrum of acquired and congenital neurological disorders.[8] While stroke recovery remains the primary area of investigation due to its high global prevalence, BCI protocols are now being extensively applied to other conditions, including spinal cord injury, traumatic brain injury, multiple sclerosis, cerebral palsy and neurodegenerative conditions like Parkinson's disease.[9] However, as visible in most of research fields, the persistent expansion of scientific literature has been partially restructuring the landscape of research, potentially generating a paradox, in which an abundance of information risks to end up obscuring, rather

than illuminating, the path to genuine insight.[10] Certainly, the use of the systematic reviews and meta-analyses supports the evaluation of literature evidence, but the conclusions in most of cases obliges to refer to the primary studies to elucidate a study subject.[11] Furthermore, traditional methods for identifying relevant studies rely on the refined intuition of experts, a process as indispensable as it is difficult to scale. Working from this tension, we propose a shift in perspective: treating the body of scientific literature not as a collection of juxtaposed texts, but as a structured semantic space with its own internal geometry. By integrating lexical evaluation with Principal Component Analysis (PCA), we analyze whether the relevance defined by human expertise emerges as a structural property of the lexical network itself, allowing us to map the underlying topography of scholarly impact.[12,13]

Materials and Methods

The method adopted for this study was the Lexical Network Based on Graph Theory (LENGTH). This methodological approach enables the modeling of the literature as a complex system, where both articles and semantic terms are conceptualized as nodes, and the presence of a word in a paper is represented as edge.[12] The resulting network, therefore, encoded semantic relationships indirectly through shared lexical structures: papers sharing similar vocabularies became connected through common word nodes, enabling the analysis of the literature as a graph-theoretical semantic system rather than as independent textual units. We performed the literature research in the PubMed database, using the specific Boolean query syntax "brain computer interface" AND rehabilitation. The temporal window was restricted to the last decade and the article type was limited to Randomized Controlled Trials (RCT). For every paper meeting these inclusion criteria, only titles and abstracts were considered to extract semantic data. To build the lexical analysis, besides the keywords used in the query, we selected additional words based on their pertinence with the topic and a frequency in the articles comparable with the frequency of the keywords. This selection was executed by the freeware software TXM 0.8.2 (2010-2021 ENS de Lyon, University of Franche-Comté, CNRS). Hence, we built a rectangular matrix, where one axis represented the individual scientific articles and the other represented the selected lexical terms. Inside the matrix, the presence or absence of a specific word, within the title or the abstract, was coded as a dichotomous variable (respectively 1 or 0).[12] This structured matrix was imported into Gephi (version 0.10.0) and Cytoscape (version 3.10.3), two open-source graph visualization and manipulation programs. For each word and paper, we calculated the different network variables including: weighted degree, authority, average shortest path length, betweenness centrality, bridging centrality, bridging coefficient, closeness centrality, eccentricity, eigen centrality, harmonic closeness centrality, hub, neighborhood connectivity, page ranks, partner of multi edged node pairs, radiality, stress, topological coefficient. Considering the purpose of this work, aimed to assess the features of the papers, to assess the relevance of each variable, a major methodological worry should be considered: the confounding effect of document size and lexical richness. In a few words, larger abstracts may artificially exhibit higher centrality values independently of their semantic role within the literature. If left unaddressed, size-related variance would dominate the multivariate space and systematically favor longer documents over shorter but conceptually focused contributions, introducing a structural bias that has no meaningful semantic interpretation. To minimize this effect, each metric was regressed against node weighted degree, which represented the number of lexical associations of each paper. Residuals from these regressions were extracted and used for subsequent analyses. This procedure effectively centered the variables and isolated structural properties independent of the total number of connections. We applied PCA on the residuals, using the correlation matrix, initially considering the complete array of metrics.[13] These metrics collectively capture global integration within the network, influence and hierarchical positioning, mediation between regions, peripheral positioning, local redundancy, and neighborhood structure. The use of PCA allows a synthetization of the numerous variables, better guiding the interpretation of the results.[13] PCA was performed using the correlation matrix, which implicitly standardizes variables to unit variance and ensures equal contribution of each metric independently of its original scale or dispersion. No rotation method was applied, allowing direct interpretation of the native orthogonal structure of the components. To ensure the robustness of the model, we performed a thorough collinearity control, excluding variables with pairwise correlations exceeding 0.7. This threshold was selected as a conventional balance between parsimony and information retention. The final variable set included: betweenness centrality, bridging centrality, closeness centrality, eccentricity, eigenvector centrality, partner multi-edge node pairs, and topological coefficient, preserving conceptually distinct dimensions of network structure while minimizing redundancy. They represented distinct domains of global integration and local mediation. Taken individually, each metric illuminates a distinct facet of a document's structural role: betweenness centrality identifies elements that serve as semantic bridges between otherwise disconnected regions; bridging centrality reflects lexical bridging between conceptually distant, poorly connected network regions; closeness centrality reflects how efficiently a paper can access the entire lexical network; eccentricity characterizes the maximum conceptual distance separating a paper from the periphery of the network; eigenvector centrality captures the quality of a node's connections by weighting neighbors according to their own centrality; partner multi-edge node pairs measures the multiplicity of shared word nodes between document pairs; and topological coefficient quantifies local redundancy through neighborhood overlap between neighboring nodes.[12] Variance inflation factor analysis was subsequently performed to assess residual multicollinearity: most variables showed values below 2, while closeness centrality showed mod-

erate values around 3, indicating acceptable independence among predictors and supporting the suitability of the final dataset for dimensionality reduction. Each retained variable was selected not solely on statistical grounds but also on the basis of conceptual non-substitutability. Hence, a new PCA was performed only with these final variables. The stability of this semantic space was confirmed by the high correlation ($r > 0.9$) between PCA solutions before and after variable reduction, indicating that the identified dimensions are fundamental features of the network's topology. Finally, articles were labeled as relevant or non-relevant based on the judgment of two independent evaluators, with two different levels of research experience (more than 15 years and less than 5 years). Each paper was classified as relevant or not relevant for its application in rehabilitation, respectively labeling it as 1 or 0. A study was considered relevant if the main topic and outcome measures included clinical investigations and if its translation in clinical activity was potentially direct. In case of discordance between the two researches, a third evaluator was independently involved for the definitive paper classification. The distribution of articles within the PCA space was subsequently visualized through scatterplots using PC1 and PC2 coordinates, and mean values were computed separately for the two article groups.
Statistical analyses were performed by using JASP software (version 0.96, University of Amsterdam).

Results

A totality of 50 papers was found on PubMed, but a paper was excluded because of its retraction. The final number of considered papers was 48 after the matrix building.[14-61] This was due to the absence of the selected words in a further paper. Indeed, in this last excluded paper the topic was far from the argument treated in this review.[62] The additional words selected were: FUNCTION, LIMB, MOTOR, STROKE, TRAINING, UPPER. The analyzed network exhibited a compact structure, characterized by identical eccentricity for all the words (a value of 3), indicative of a graph with a small diameter and high interconnection between terms (Figure 1). The word nodes with the highest structural centrality were MOTOR and FUNCTION. The first one had the highest degree and the highest eigenvector and betweenness centrality, indicating a central role both in terms of frequency and mediation between the different concepts. FUNCTION displayed the highest closeness centrality and comparable betweenness, suggesting a particularly favorable position in reaching all other nodes in the network. The term STROKE emerged as the main clinical reference, with a high degree, high eigenvector centrality, and significant betweenness, positioning itself as a central node within the network. The term TRAINING displayed intermediate degree values but significant betweenness, indicating a link between the more theoretical and outcome-oriented concepts. The technological terms BCI and BRAIN-COMPUTER were well integrated into the network, with high closeness centrality and significant betweenness, while maintaining a lower eigenvector centrality than the main clinical-functional nodes. Anatomical terms, such as UPPER and LIMB, displayed lower degree and centrality, appearing as more peripheral nodes (Figure 2).
The PCA of the papers identified two principal components explaining a cumulative variance of approximately 61.05%, with PC1 accounting for 42.52% and PC2 for 18.53% (Figure 3). The loading structure revealed a highly interpretable organization of the semantic space. PC1 was characterized by strong positive loadings for closeness centrality (0.91) and bridging centrality (0.82), a moderate positive contribution from partner multi-edge node pairs (0.53), and negative loadings for topological coefficient (−0.77), eccentricity (−0.61), and betweenness centrality (−0.49). This component therefore represents a continuum between globally integrated papers and structurally peripheral or locally redundant nodes: high PC1 values corresponded to articles occupying highly integrated positions within the semantic network, whereas low PC1 values corresponded to papers characterized by greater peripheral distance or local redundancy. PC2 was dominated by eigenvector centrality (0.89), with an additional negative contribution from betweenness centrality (−0.59), capturing hierarchical influence and structural prominence within the network and distinguishing highly influential nodes from those acting primarily as intermediaries. PC1 and PC2 remained orthogonal, confirming the presence of two distinct and non-overlapping latent structural dimensions. Among the 48 papers included, 30 were considered relevant. Relevant and non-relevant articles showed substantial overlap within the PCA space, indicating the absence of clear linear separability. Nevertheless, systematic directional differences emerged. Mean PC1 and PC2

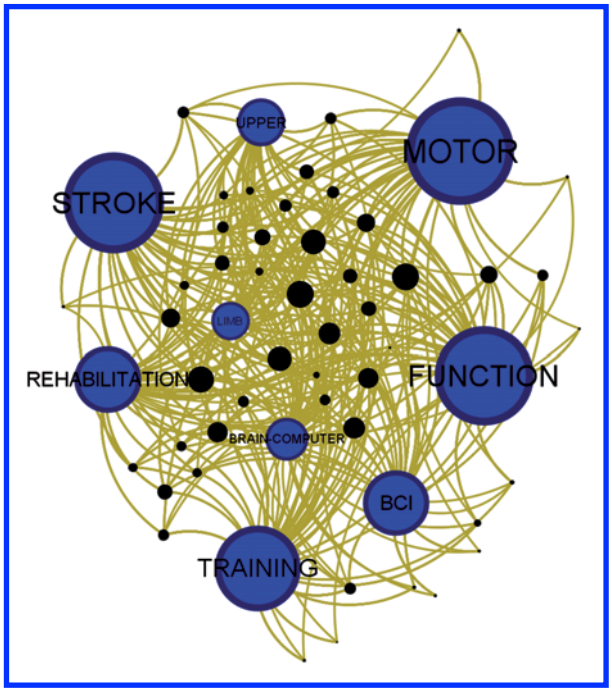

Figure 1. *Lexical network based on graph-theory.*

values differed consistently between groups: relevant articles showed PC1 = +0.05 and PC2 = −0.06, whereas non-relevant articles showed PC1 = −0.08 and PC2 = +0.10 (Figure 4). This indicated that relevant articles tended to occupy regions characterized by higher integration and lower hierarchical influence. Scatterplot visualization confirmed this trend, the quadrant defined by positive PC1 and negative PC2 values mostly populated by relevant articles, while non-relevant articles appearing more spatially dispersed.

Label	degree	betweenness centrality	bridging centrality	closeness centrality	eigencentrality	partner multi edged node pairs	topological coefficient
MOTOR	172	270.11372	0.00012	0.686747	1	33	0.746875
STROKE	163	208.938923	0.000112	0.6	0.926632	32	0.797794118
FUNCTION	160	268.862432	0.000135	0.721519	0.911346	32	0.720238095
TRAINING	136	200.228326	0.000127	0.640449	0.670979	29	0.75
REHABILITATION	107	91.762893	0.000121	0.626374	0.650312	25	0.784722222
BCI	104	106.414487	0.000129	0.522936	0.62447	21	0.796296296
UPPER	78	34.553008	0.000097	0.542857	0.492041	17	0.870689655
BRAIN-COMPUTER	71	102.184651	0.000228	0.76	0.343382	24	0.707386364
LIMB	66	26.94156	0.000108	0.513514	0.408378	15	0.889423077

Label	degree	betweenness centrality	bridging centrality	closness centrality	eigen centrality	Partner of multi edged node pairs	topological coefficient
MOTOR	169	260.912416	0.000124	0.682927	1	32	0.743589744
STROKE	158	197.054236	0.000117	0.595745	0.914382	31	0.795454545
FUNCTION	155	255.588264	0.000141	0.717949	0.899136	31	0.716463415
TRAINING	135	197.202485	0.000132	0.636364	0.676512	29	0.746527778
REHABILITATION	105	88.557856	0.000126	0.622222	0.649666	24	0.782142857
BCI	104	106.589031	0.000134	0.528302	0.63427	21	0.796296296
UPPER	77	33.578312	0.0001	0.538462	0.493744	17	0.870535714
BRAIN-COMPUTER	69	97.996748	0.000239	0.756757	0.338404	23	0.703488372
LIMB	62	23.520652	0.000112	0.509091	0.394112	14	0.89

Figure 2. *Variables of the word nodes.*

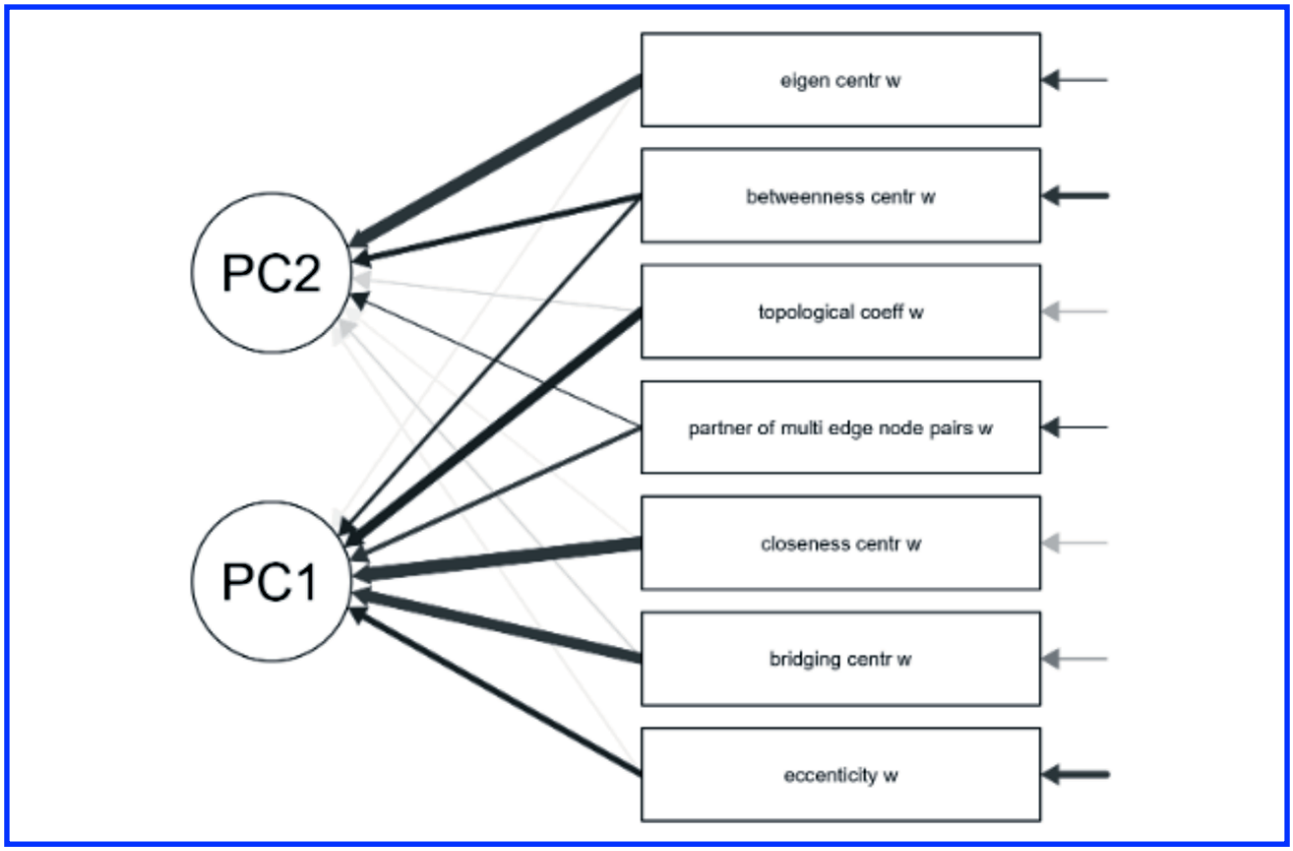

Figure 3. *Path diagram of the PCA.*

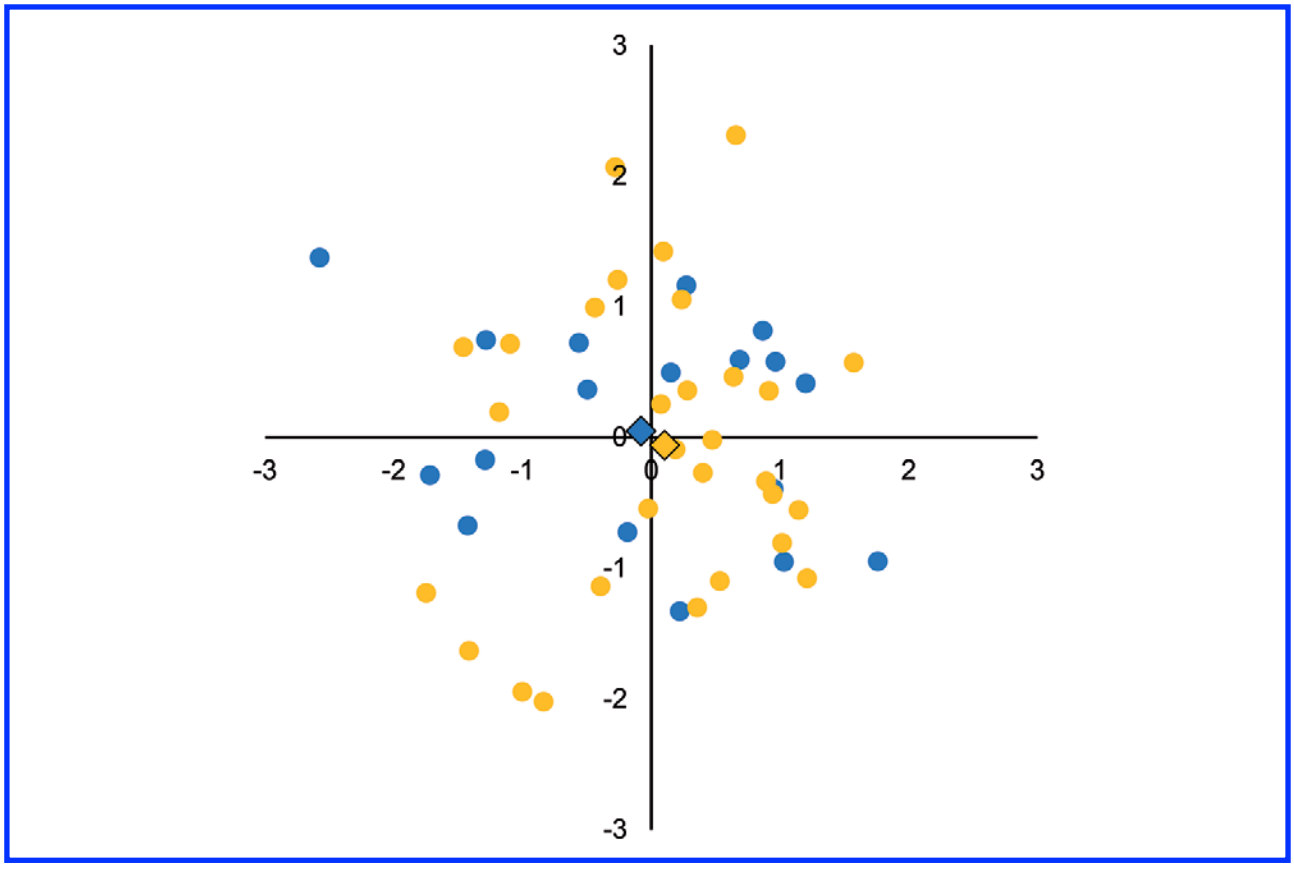

Figure 4. *Distribution of the papers of the two groups, based on PCA. The rhombuses represent the mean values of the two paper groups (relevant yellow/not relevant blue based on researchers' classification).*

Discussion

The exponential growth of scientific literature has progressively increased the difficulty of identifying studies that are genuinely relevant to a specific research or clinical question. Traditional evidence synthesis strategies continue to rely predominantly on expert-driven selection procedures, which remain indispensable but are intrinsically influenced by subjective interpretation, disciplinary background, and contextual priorities.[63] Although systematic review methodologies aim to reduce bias through predefined criteria, the increasing dimensionality and heterogeneity of scientific production challenge the scalability and reproducibility of purely manual approaches. In parallel, advances in computational text analysis and network science have enabled the representation of scientific literature as structured relational systems, but with unclear results.[10] Within these frameworks, articles may be additionally considered interconnected components of a semantic ecosystem, where lexical overlap, conceptual proximity, and structural relationships may reveal latent patterns that are not directly observable through conventional reading-based approaches. Graph theory provides a particularly suitable framework for this purpose because it enables the extraction of quantitative topological descriptors capable of characterizing the structural role of individual documents within a semantic network.[12] Metrics such as centrality, bridging properties, local redundancy, and integration may capture distinct dimensions of how a paper interacts with the broader conceptual organization of the literature. On the other hand, PCA offers a way to project multidimensional topological information into a lower-dimensional semantic space while preserving the dominant variance structure of the data.[13] In this context, PCA does not merely serve as a visualization tool but rather as a method for identifying latent structural dimensions underlying the organization of the literature itself.

Our analysis of the lexical network of RCTs on brain-computer interfaces in rehabilitation highlights a coherently organized and structurally integrated literature. The reduced eccentricity of the graph suggests a compact conceptual domain, in which the main terms are closely linked. The centrality of MOTOR and FUNCTION indicates that motor and functional recovery represents the conceptual core of the scientific narrative, appearing not only as an outcome but as an organizing element of the entire rehabilitation discourse.[24] The central role of STROKE suggests that this clinical condition constitutes the primary application area around which evidence on brain-computer interfaces develops.[19] The terms TRAINING and

REHABILITATION serve as conceptual mediators, connecting technological and neurophysiological aspects to clinical and functional objectives.[26] The structurally relevant presence of BCI and BRAIN-COMPUTER indicates that technology is fully integrated into the scientific narrative, but remains subordinate to rehabilitation objectives, rather than constituting an independent end. Overall, the network portrays a goal-oriented literature, in which technology, rehabilitation process, and functional outcomes are strongly interconnected, outlining a coherent conceptual framework focused on the clinical application of brain-computer interfaces in rehabilitation.[24]

PCA findings suggest that expert-defined relevance does not emerge as a sharply separable categorical property within the semantic network of the literature. Instead, relevance appears as a spatial tendency characterized by preferential positioning within a multidimensional topological landscape. Relevant articles do not occupy an exclusive territory but instead exhibit a systematic directional bias toward a specific region of the PCA space, coexisting with non-relevant articles across much of the topological landscape.[22] The structural signature of relevant articles, higher PC1 and lower PC2, translates into a coherent and theoretically grounded interpretation. Higher PC1 values reflect stronger global integration within the semantic network: articles that share vocabulary broadly across the corpus, that serve as lexical bridges between different thematic clusters, and that are reachable from many other documents via short conceptual paths.[35] This structural profile is consistent with what one would expect of articles that are genuinely embedded in the operational discourse of a specific domain. Such papers employ the field's established terminology, engage with its core conceptual distinctions, and contribute to the shared lexical infrastructure that defines the domain's boundaries. Their integration is not merely quantitative, like a function of length or vocabulary breadth, but also qualitative, reflecting alignment with the conceptual architecture of the field as a whole. Lower PC2 values, reflecting reduced eigenvector centrality relative to betweenness, suggest that relevant articles tend not to occupy the most hierarchically prestigious positions within the network's authority structure. This finding is initially counterintuitive: one might expect the most relevant articles to also be the most influential. However, the dissociation becomes interpretable when one considers the different epistemic functions that network position can reflect. Articles with high eigenvector centrality are connected to other highly central documents and they participate in the densely interconnected core of the literature, which is often populated by theoretical reviews, methodological frameworks, and landmark papers that have shaped the field's foundational assumptions. These works are undoubtedly important, but their importance is of a different order than operational relevance to a specific research question.[53] Relevant articles, in this interpretation, are those that inhabit the empirical and applied interior of the domain, without necessarily anchoring its theoretical superstructure. This distinction resonates with a broader epistemological tension in evidence synthesis between breadth of influence and depth of domain specificity. A highly cited methodological paper may be essential background reading for an entire discipline while remaining only tangentially relevant to a focused systematic review on a particular intervention. Conversely, a modestly cited empirical study that directly addresses the review's population, intervention, comparator, and outcome may be of central relevance despite occupying a less prestigious network position. The PCA space appears to capture something of this distinction: PC1 encodes domain embeddedness, while PC2 encodes a form of disciplinary prestige that, while correlated with broad importance, does not necessarily track operational relevance. From a methodological standpoint, the integration of graph theory and dimensionality reduction proved effective in transforming a high-dimensional and intercorrelated set of topological features into an interpretable two-dimensional semantic space that retains over 60% of the original variance. The use of residuals was critical in ensuring that the identified dimensions reflected genuine structural variation rather than document-size effects, and its importance should not be underestimated in any replication of this framework. Without this correction, the PCA space would be dominated by a single size-related axis that conflates lexical richness with semantic positioning, rendering the remaining components difficult to interpret. Similarly, the decision to use correlation-based rather than covariance-based PCA ensured that metrics operating on very different numerical scales contributed equally to the latent structure, preventing the inadvertent dominance of any single measure. The stability of the PCA solution across variable reduction procedures is particularly noteworthy. The high correspondence between components derived from the full variable set and the reduced seven-variable set confirms that the identified latent dimensions are intrinsic organizational properties of the literature rather than artifacts of the specific metric selection. This robustness has practical implications: it suggests that the framework can tolerate reasonable variation in the initial metric set without fundamentally altering the semantic map it produces, which is an important property for a methodology intended to generalize across different corpora and research domains.

The practical implications of this framework for systematic review methodology are significant. The identification of a preferential region in PCA space associated with relevant articles opens the possibility of topologically informed screening prioritization: articles positioned in regions of high PC1 and low PC2 could be flagged for priority review, while those occupying the opposite quadrant could be deprioritized without exclusion. This would not eliminate the need for expert review but could substantially reduce its burden, particularly in large corpora where exhaustive manual screening is prohibitively time-consuming. In a few words, the methods may be useful as an adjunctive support for the paper evaluation. The key advantage of this approach over purely keyword-based or citation-based filtering is that it captures structural relationships that are not reducible to the presence of specific terms or to formal citation linkages, potentially surfacing relevant articles that would be missed by conventional search strategies.

Several limitations constrain the generalizability of the present findings and should inform future work. The se-

mantic network is fundamentally conditioned by the lexical preprocessing pipeline applied to the corpus: stopword removal, term weighting, and vocabulary thresholds all influence network topology and therefore the derived metrics and PCA structure. The present analysis does not systematically explore the sensitivity of the results to these choices, which represents an important direction for future methodological investigation. Different preprocessing strategies may yield substantially different networks, and it cannot be assumed that the structural dimensions identified here would emerge consistently across all preprocessing configurations. A systematic sensitivity analysis across preprocessing variants would be necessary to establish the robustness of the framework beyond the specific implementation reported here.

The sample size of the present study is acknowledged as a limiting factor in the stability of supervised classification models. Furthermore, human classification of the relevance may be susceptible of mistakes that can influence the final results. Replication on larger corpora, ideally spanning multiple systematic reviews across different domains, would allow more definitive conclusions about the generalizability of the identified structural dimensions and their relationship to expert-defined relevance.

Finally, the use of linear dimensionality reduction through PCA imposes a structural assumption on the data: that the dominant sources of variation in the topological space are linearly organized. Semantic relationships in scientific literature are unlikely to be purely linear, and it is plausible that nonlinear embedding methods would reveal additional structure not captured by the present approach. Future studies should explore whether nonlinear representations yield more coherent separation between relevant and non-relevant articles, and whether the structural dimensions they identify are interpretable in terms comparable to those emerging from the linear PCA solution reported here.[64]

Overall, the present framework demonstrates that LENGTH and PCA encode interpretable signals related to expert-defined relevance, even when that signal does not support clean categorical classification. Relevance emerges not as a discrete attribute but as a positional tendency within a multidimensional semantic landscape.

Finally, beyond its immediate application to systematic review screening, the present framework may offer a broader utility as a structured support tool for evaluating the contextual weight of individual contributions within a given literature. The positional information derived from the semantic network could complement traditional appraisal criteria, providing reviewers with a quantitative index of a paper's domain embeddedness that is independent of citation counts or journal prestige. Looking further ahead, the semantic space generated by this approach represents a potentially valuable resource for training artificial intelligence systems designed for automated literature analysis: by providing labeled positional data that encodes the structural relationship between topological features and expert-defined relevance, this framework could contribute to the development of more domain-aware, interpretable models for evidence screening and knowledge synthesis.[65]

List of abbreviations

BCI, brain-computer interface
LENGTH, Lexical Network Analysis Based on Graph Theory
PC1, first principal component
PC2, second principal component
PCA, principal component analysis
RCT, randomized controlled trial

Contributions

Conceptualization, methodology, writing—original draft preparation, Daniele Coraci and Gianluca Regazzo; validation, formal analysis, software, visualization, Daniele Coraci; writing—review and editing, supervision, Stefano Masiero. All authors have read and agreed to the published version of the manuscript

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Conflicts of interest

The authors declare no conflicts of interest.

Ethics approval and consent to participate

Not applicable.

Data availability statement

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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