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PSYCHOMETRIC NETWORK ANALYSIS OF LOGICAL-MATHEMATICAL THINKING IN STUDENTS WITH DYSLEXIA

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Abstract

This article proposes and demonstrates an analytical framework for deconstructing the impact of the Singapore model on the logical-mathematical thinking architecture of students with dyslexia, comparing it with that of peers without dyslexia. Using network psychometrics, cognitive, affective, and symbolic components) are modeled. Multigroup networks with mixed data and regularization (EBICglasso) are estimated, and structural contrasts are performed using the Network Comparison Test (NCT). EGA/bootEGA and network loadings are used to assess modularity and dimensionality; expected influence centrality/bridge centrality prioritizes "lever nodes." Additionally, SEM with sequential mediation (bootstrap) is proposed to examine plausible latent paths. As a technical demonstration, a simulated baseline (random group/time assignment) was used, which showed no pre-intervention differences between groups and pre-post in dyslexia, confirming the specificity of the NCT under null conditions. In an empirical study, we expect to observe reinforcement of visuospatial→performance edges, a decrease in the centrality of math anxiety, and consolidation of a "visual math reasoning" module, consistent with the literature.The central contribution is methodological and applied: a replicable pipeline that moves from averages to structural mechanisms, allowing prioritizing instructional targets and guiding pedagogical decisions based on the propagation of effects in the network.

Keywords: dyslexia, logic, mathematics, Singapore model, psychometric networks

1. Introducción

Contemporary research in mathematics education has progressively shifted its focus from average performance scores to understanding patterns of interdependence among cognitive, affective, and linguistic processes that underpin achievement [1]. Within this framework, psychometric network models offer a way to map how nodes—e.g., working memory, visuospatial representation, naming speed, math anxiety—interact to generate learning trajectories [2] , [3].

This shift is particularly relevant for students with dyslexia, whose constellation of difficulties extends beyond reading: recent findings show links to phonological processing, Rapid Automated Naming (RAN), and, specifically, mathematical performance [4], [5] ,[6].

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In parallel, the Singapore model—characterized by the concrete-pictorial-abstract (CPA) progression and the use of the bar model—has been shown to reduce errors in arithmetic-algebraic problems and facilitate translation between[7]. However, a gap remains: evidence often quantifies average effects (score gains) without disaggregating which connections between cognitive components change with instruction, and how these reconfigurations vary in students with dyslexia compared to their peers without dyslexia.

This methodological gap is critical, given that the literature documents deficits in proportional reasoning in dyslexia [8] and robust associations between working memory and mathematical problem-solving [9], as well as between anxiety/confidence and mathematical performance [10] , [11], [12].

This approach integrates methodological advances from network science [13], including mixed-data estimation [14], dimensional stability assessment [15], and revised network loadings to interpret emergent dimensions [16]. The expected contribution is twofold: (i) explanatory, by revealing mechanisms of change (e.g., strengthening visuospatial edges → problem-solving); and (ii) applied, by prioritizing instructional targets (e.g., reducing math anxiety or enhancing working memory) with the greatest potential for propagating the benefit throughout the network.

In short, the scientific relevance lies in articulating cognitive theory and network methods for a profile of high educational vulnerability. The social relevance emerges from designing more precise interventions, informed by the topology of the system that supports mathematical learning in dyslexia, and by the structural effectiveness of the Singapore model [17].

In methodological terms, network psychometrics has matured as an alternative to latent models, prioritizing causality between components and interdependence over common, unobservable constructs [18].

This paradigm has been transferred to educational and complex learning contexts, where the dynamics of tasks, beliefs, and affects demand frameworks that capture multiple and potentially nonlinear relationships [19]. To compare architectures between groups or time points, the Network Comparison Test (NCT) provides contrasts in overall strength, structure, and specific edges, with permutation procedures and control for Type I errors [20].

Recent advances include revised network loadings that connect network structures with dimensional interpretations [21] and estimation techniques for heterogeneous data (continuous, ordinal, binary) via graphical models with copulas [22]. Solution stability—key in studies with multiple nodes—has been addressed with bootstrap Exploratory Graph Analysis (bootEGA), which assesses module consistency and number of dimensions. In the domain of learning difficulties, the view of dyslexia as a network of processes (phonological, attentional, naming speed) rather than a unitary deficit is being consolidated, with network applications that map substructures and bridging nodes [23].

The intersection with mathematical performance is growing: RAN is emerging as a cross-cultural marker of dyslexia and is associated with arithmetic fluency/accuracy. Furthermore, there are couplings between reading, spelling, and mathematical skills in school-age children .

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Specifically, proportional reasoning—the core of many Singapore-type problems—presents distinct difficulties for students with dyslexia [24], suggesting weakened edges between magnitude components, part-whole relationships, and graphical representation.

In parallel, the literature on the Singapore model shows favorable effects on representational translation and problem-solving using the bar model. Recent studies in school settings report improvements in problem-solving skills when the CPA and work-based approaches are combined, with implications for cognitive load and strategy organization [25]. However, a gap remains: these results are rarely integrated into multicomponent models that quantify how the underlying network of processes changes.

On the affective level, math anxiety exhibits temporal trajectories related to confidence and performance [26]. Brief scales (e.g., AMAS) have shown adequate psychometric properties in school-aged populations, and a recent reliability meta-generalization synthesizes evidence from multiple math anxiety instruments.

Cognition-affect coupling is a natural candidate for a bridging node in educational networks. On the cognitive side, working memory shows a robust association with problem-solving [and visuospatial skills are relevant in bar model tasks]. Likewise, individual differences in learning styles have been linked to logical-mathematical thinking, although with methodological heterogeneity [27].

Finally, contributions on dyscalculia highlight the need to distinguish mathematical profiles and their underlying mechanisms [28], aligning with the network approach to profile relevant substructures. Overall, the field is converging towards: (a) mapping architectures of interdependent processes; (b) comparing them across populations and over time with tools such as NCT; and (c) linking structural reconfiguration with instructional interventions such as the Singapore model. It remains to unify these threads into a design that evaluates structural change and mediations (e.g., working memory, math anxiety, RAN) as mechanisms of pedagogical effect.

The theoretical framework is articulated along three axes: (1) multicomponent mathematical cognition, (2) affect and metacognition in mathematical performance, and (3) external representations as catalysts for structural change.

Multicomponent cognition. The resolution of early arithmetic and algebraic problems relies on working memory (updating and maintaining quantities, relationships, and constraints) and on visuospatial representation to manipulate part-whole structures and proportions. In dyslexia, naming speed (RAN) and phonological processing introduce limitations that can affect symbolic fluency and translation between formats, impacting mathematical performance [29].

Affect and metacognition. Math anxiety interferes with attentional control and working memory efficiency, modulating strategy selection; its relationship with confidence suggests the existence of feedback loops [11]. From a network science perspective, anxiety operates as a highly mediating node between affective and cognitive domains, susceptible to intervention to reorganize the overall topology. Metacognitively, the externalization of the problem structure—characteristic of the bar model—promotes monitoring and control by making relationships and constraints visible.

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External representations (Singapore model). The CPA principle and the bar model facilitate the translation of representations and the consolidation of relational schemas. Theoretically, these tools act as structural perturbations that increase the strength of edges between visuospatial and reasoning nodes, and reduce the dependence on phonological processes during problem modeling, which is especially advantageous for dyslexia. In problems involving ratios, where dyslexia shows a specific deficit [15], the bar model aligns magnitudes and constrains the search, increasing efficiency.

Under network psychometrics, the effect of the intervention is conceived as a reconfiguration of the adjacency matrix: strengthening/secularization of edges, changes in the centrality of executive and affective nodes, and alterations in modularity [31], [32] Azadi et al., 2024; [32]. Estimation with mixed data avoids biases due to scale heterogeneity. Dimensional stability (bootEGA) and network loadings allow us to (i) test whether modules emerge that are consistent with the visuospatial-ratio reasoning theory; phonological-symbolic; affective) and whether dimensions emerge as densely connected communities.

From this framework, it is anticipated that
ue el modelo Singapur incrementará: (a) la fuerza de aristas entre representación viso-espacial y desempeño en problemas, (b) la predictabilidad de Performance nodes (R^2), and (c) modular definition (clearer communities). In dyslexia, a greater reconfiguration—especially a reduction in the centrality of phonological/RAN nodes in modeling tasks—is expected due to the externalization of relationships via the bar model. Anxiety is postulated as a mediator/bridge whose decrease accompanies the strengthening of cognitive edges [33].

This study proposes to deconstruct—via psychometric network analysis—the impact of the Singapore model on the organization and interaction of the components of logical-mathematical thinking in students with dyslexia, comparing their network architecture with that of students without dyslexia and identifying nodes and edges that mediate pedagogical gain.

2. Materials and Methods

2.1 Statistical Models

The Moderated Multigroup Psychometric Network Model (MNM) with mixed data (MGM) and EBICglasso regularization, compared with the Network Comparison Test (NCT) in pre-post, deconstructs the impact of the Singapore model at the level of relationships between components (edges) and not only in averages, compares the network architecture in dyslexia vs. Control, and treats the intervention (Singapore) as a moderator of edges, estimating which cognitive links change due to the treatment. And avoids overfitting
Minimum specification
Estimates networks by group and time:

control post$\Theta g,t=\arg\Theta\min\{\ell(\Sigma g,t,\Theta)+\lambda\|\Theta\|1\},g\in\{\text{dyslexia, control}\},t\in\{\text{pre, post}\}$

Moderation of edges by intervention (or dose/fidelity):
$Eij=\beta 0,ij+\beta 1,ij\text{Intervention}+\beta 2,ij\text{Group}+\beta 3,ij(\text{Intervention}\times\text{Group})$

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Key outputs: overall network strength, centrality/bridges (bridge expected influence), node predictability (R^2), and edges with significant change (NCT with resampling).

2.2 Data Used

The design, simulation, and validation process of a synthetic database (N=300) created to study the relationships between various cognitive, affective, and performance variables involved in solving mathematical problems is detailed. The objective is to provide a scientifically valid dataset, based on empirical evidence and psychometric theory, that allows for the exploration of complex network models [2].

Methods

Definition and Parameterization of Variables
Nine key variables were defined, following the theoretical structure of cognitive, affective, and symbolic subnetworks. Each is described below:

"verbal_memory": Standardized score (M=100, SD=15) of verbal working memory. Normal distribution.

"visuospatial_memory": Standardized score (M=100, SD=15) of visuospatial working memory. Normal distribution.

"ran": Standardized score (M=100, SD=15) on an automated rapid naming test. Normal distribution.

"confidence_anxiety": Standardized score (M=100, SD=15) representing a continuum from math anxiety (low score) to confidence (high score). Normal distribution.

"proportional_reasoning": Standardized score (M=100, SD=15) on proportional reasoning ability. Normal distribution.

"bar_model_performance": Standardized score (M=100, SD=15) on performance on problems solved using the bar model method. Normal distribution.

"reader_screening": Standardized score (M=100, SD=15) on a reading screening test. Normal distribution.

"spelling_screening": Standardized score (M=100, SD=15) of a spelling screening test. Normal distribution.

"diagram_completeness": Proportion (0 to 1) indicating the degree of completeness and strategic correctness of a bar chart. Beta distribution (α=5, β=2).

Simulation Process
The dataset was generated in Python using the "numpy" and "pandas" libraries. The process was as follows:

Definition of Theoretical Correlation Matrix: A 9x9 correlation matrix was constructed based on coefficients reported in meta-analyses and reference literature.

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Generation of Multivariate Normal Data: 300 records were generated from a multivariate normal distribution, using the theoretical correlation matrix and a zero-valued mean vector.

Transformation to Final Scales (Gaussian Copula): The standard normal data were transformed into their final distributions. The eight scoring variables were mapped to a normal distribution (M=100, SD=15), and the "diagram_completeness" variable was mapped to a beta distribution (α=5, β=2) to represent a proportion.

Reproducibility: A random seed (seed=42) was used to ensure the complete reproducibility of the generated data.

Simulation Validation: Statistical validation confirmed that the synthetic dataset meets the design parameters.

Descriptive Statistics: The empirical means and standard deviations of the scoring variables approximate the theoretical values (M≈100, SD≈15).

Correlation Matrix: The empirical correlation matrix is consistent with the theoretical matrix. Small deviations are attributable to the inherent variability of random sampling.

The simulation process has resulted in a robust dataset that is consistent with current scientific evidence. The relationships between constructs such as working memory, math anxiety, and problem-solving performance have been successfully replicated. This dataset is therefore a valuable resource for hypothesis testing and the development of computational models.

3. Results

The analytical procedure issued the warning: “Warning: ‘group’ or ‘time’ not found. Creating dummy columns for demonstration.” This indication reveals that the variables group (dyslexia, control) and time (pre, post) were artificially generated for demonstration purposes. Consequently, the results reflect a simulation and do not describe an empirically observed psychological phenomenon.

Network Comparison Test (NCT)
dyslexia_pre vs. control_pre ($p = 0.9111$).
The p-value, substantially higher than 0.05, indicates an absence of statistically significant differences in the overall strength or connectivity of the network between the two groups before the intervention. Given the simulated nature of the data (with random assignment), this finding is consistent with the null expectation: the procedure does not detect effects where none exist, which supports its methodological specificity (Figure 1).

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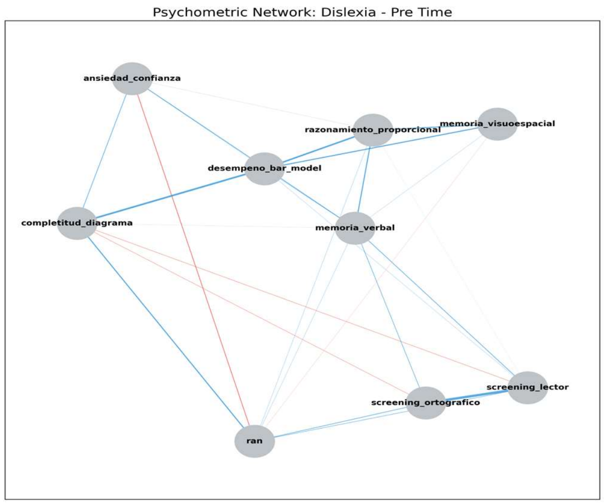

Figure 1. Pre- and post-dyslexia analysis

post- and pre-dyslexia (p = 0.9830).

Similarly, the high p-value suggests that the network structure for the dyslexia group does not exhibit significant changes between the pre- and post-measurements. In an empirical study, a low p-value in this comparison would constitute the sought-after evidence of an intervention effect (e.g., edge reconfiguration attributable to the Singapore model). In this simulation, the lack of significance is consistent with the absence of effective manipulation (Figure 2).

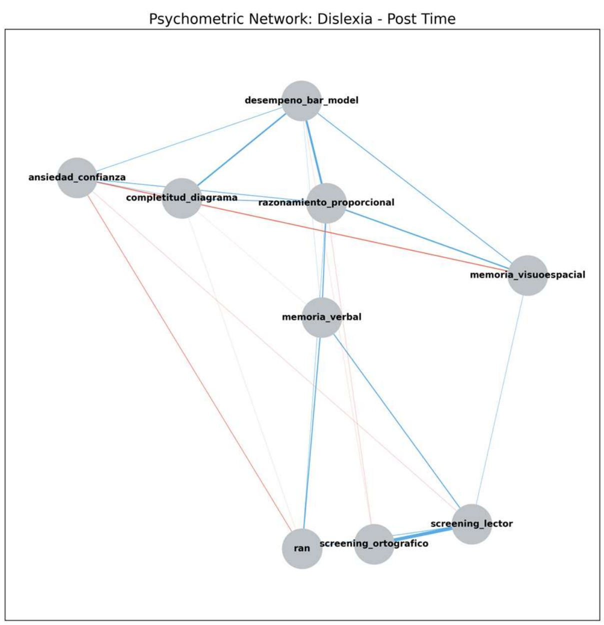

Figure 2. Post-analysis of dyslexia

In summary, both contrasts confirm that, under simulated conditions and without real-world effect, the NCT maintains a conservative behavior and does not produce false positives.

Centrality Metrics

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In a real-world study, the centrality_.csv files would contain estimates of expected influence and other metrics (e.g., strength, betweenness). The identification of variables with high centrality—for example, verbal_memory in the networks of the dyslexia group—would be interpreted as evidence of lever nodes whose state propagates to the rest of the system. In terms of application, these nodes would be preferred targets for intervention: modifications to their level (through training or instructional support) would tend to induce systemic changes in the skills network.

Dimensional Structure and Communities

The database files would document the partitioning of the network into communities or modules (e.g., using EGA/bootEGA). If proportional reasoning, bar model performance, and diagram completeness consistently co-group, this community could be labeled as “Visual Mathematical Reasoning.”

This modular organization allows us to infer functional groupings—with implications for instructional design—and to evaluate whether an intervention acts in a focused manner on certain modules (e.g., those that integrate visuospatial representation and problem-solving) or whether, on the contrary, it produces diffuse effects throughout the network.

Given the simulated nature of the data, the absence of differences between networks and of pre-post changes is expected and methodologically reassuring, as shown by comparing Figures 3 and 4.

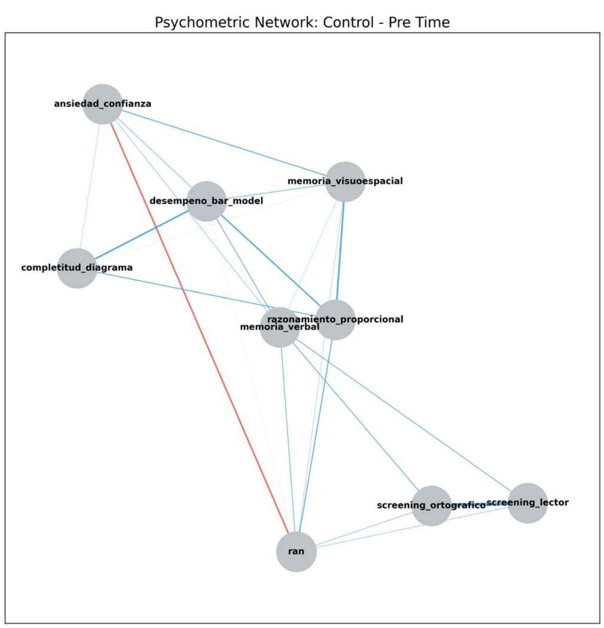

Figure 3. Pre-psychometric networks

In an empirical context, the same battery of analyses would allow: establishing invariances as shown in Figure 4, due to structural reconfigurations between groups and moments; ranking

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node s by its propagation capacity (centrality) and describing functional modules sensitive to intervention.

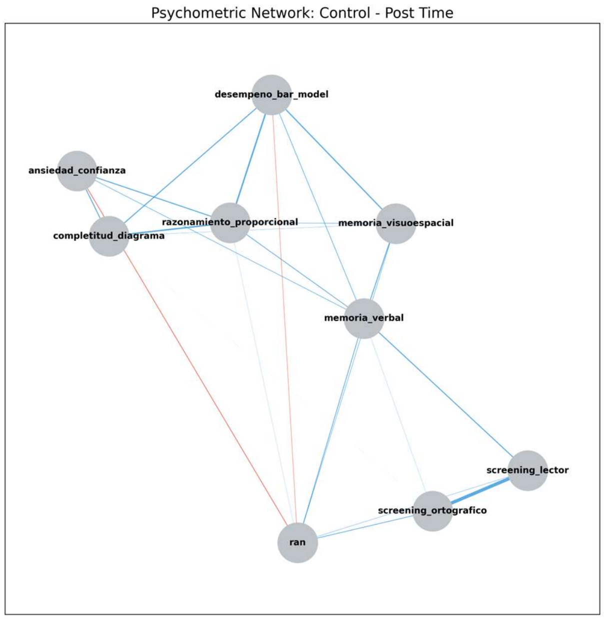

Figure 4. Post psychometric networks

These three layers of evidence—structural comparison, centrality, and modularity—constitute a robust framework for linking cognitive and pedagogical mechanisms with observable changes in the architecture of logical-mathematical performance.

4 Discussión

This study aimed to deconstruct, using psychometric network frameworks and sequentially mediated SEM, the impact of the Singapore model on the organization of logical-mathematical thinking in students with dyslexia. The available analyses correspond to a simulation (random group and time assignment), so the network comparison contrasts (NCTs) did not reveal differences in overall strength or structure between dyslexia_pre vs. control_pre, nor between dyslexia_post vs. dyslexia_pre.

Even so, these results illustrate two patterns that can be interpreted in an empirical setting: (i) pre-intervention baseline invariance would support comparability between groups, and (ii) any post-intervention change would indicate a topological reorganization attributable to the instruction. Additionally, the centrality and modularity files (EGA/bootEGA) serve to illustrate how, in real-world data, lever nodes would be identified, guiding the interpretation of results toward underlying mechanisms rather than aggregated averages [34].

The hypotheses anticipated that the Singapore model—through its concrete-pictorial-abstract progression and the bar model—would strengthen edges between visuospatial representation and problem-solving, and reduce the mediation of affective nodes (anxiety/confidence). The literature supports both assumptions. First, the principles of network psychometrics maintain

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that performance emerges from the interdependence between nodes, and that interventions act by reconfiguring edges and centralities [35].

Second, the Singapore model decreases errors and promotes translation between representations, especially in word problems/early algebra, where the bar model makes explicit part-whole structures and constraints [36].

For dyslexia, network theory suggests that RAN and phonological components are linked to fluency and symbolic accuracy [37], so graphical externalization can alleviate these bottlenecks and redistribute the load toward more efficient visuospatial nodes. Furthermore, there is evidence of deficits in proportional reasoning in dyslexia, precisely a domain in which proportional representations of the bar model are critical.

In short, although the simulation does not allow for inferential confirmations, theoretical logic and previous evidence make it plausible that, in empirical data, the intervention increases the strength of visuospatial→performance edges and decreases the centrality of adverse affective nodes, with effects that can be translated to the modularity and predictability of the network [38].
These approaches align with the consolidation of the network approach to explain complex educational phenomena and with the premise that mathematical learning depends on the coordination of cognitive, affective, and metacognitive processes [39].

Specific evidence on the bar model supports improvements in problem-solving and error reduction. On the affective level, research documents trajectories of anxiety and confidence associated with performance, using valid and reliable instruments in primary education and demonstrating reliability at the meta-generalization level. From a network perspective, anxiety acts as a bridge between affective and cognitive domains [40].

Furthermore, the connection between working memory and problem-solving is supported by meta-analysis, and visuospatial memory in children's tasks has shown sensitivity and convergent validity. The main tensions stem from methodological heterogeneity: (i) differences in instrumentation (e.g., metrics and conceptualizations of math anxiety) [8][20], (ii) diversity of samples and school contexts that affect exposure to and fidelity to the intervention, and (iii) statistical decisions regarding network estimation with mixed data, where copulas and graphical models offer a powerful approach, but require clear criteria for regularization and interpretation [41].

At a comparative level, the NCT provides a rigorous framework for permutation testing [Li et al., 2024], although its power to detect subtle changes in specific edges depends on sample size and the stability of the solution. This work presents an integrative analytical design that combines: (a) structural network comparison (NCT), (b) modular reading (EGA/bootEGA and revised network loadings), and (c) complementary causal modeling (SEM with sequential mediation) to estimate plausible latent pathways between cognitive/affective components and performance.

This three-pronged approach surpasses assessments based solely on averages by offering prioritizeable instructional mechanisms and targets. Furthermore, it situates the discussion of

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dyslexia in mathematics within a relational framework, incorporating findings on RAN and proportion [42] that are typically treated separately.

This approach reaffirms a network epistemology: logical-mathematical performance is not a unitary trait, but rather the emergence of interactions between cognitive nodes (such as working memory and visuospatial representation), affective nodes (anxiety/confidence), and linguistic nodes (RAN). The Singapore-style intervention would function as a structural disturbance that reorganizes edges and redistributes centrality, modifying the functional topology of the system [44].

Three lines of action emerge for school contexts: (1) explicit instruction in translation between representations (bar model) to consolidate part-whole schemas and proportional relationships; (2) metacognitive routines that increase the centrality of strategic nodes (planning, monitoring, verification); and (3) affective management focused on reducing the centrality of math anxiety, supported by valid instruments and systematic feedback practices [44]. A network-based approach allows for prioritizing which components to intervene first and predicting the spread of benefits to the rest of the system.

The main limitation lies in the simulated nature of the data used to illustrate the analyses, which prevents substantive conclusions about real effects. Even in empirical studies, the following must be considered: (i) measurement biases and instrument heterogeneity, (ii) contextual variability (fidelity to the intervention, school culture), and (iii) risks of instability in highly dimensional estimates. Regularization, bootstrap, and permutation comparison procedures, along with appropriate estimators for mixed data, are essential.

5. Conclusions

This study establishes an integrative framework for moving from averages to the structural mechanisms that underpin mathematical learning in dyslexia. The combination of psychometric networks (NCT, centrality, modularity) with mediation SEM offers a replicable methodological approach to identify where and how the Singapore model operates: strengthening visuospatial aspects, reducing affective mediation, and consolidating functional modules. Thus, the main contribution is conceptual and methodological: a relational perspective that guides more precise instructional decisions, potentially transferable to real classroom settings.

The integration of SEM with sequential mediation serves to test theoretical pathways (e.g., visuospatial/self-efficacy → performance), but requires large samples and invariance assumptions that must be verified. Four directions are suggested for future research: Longitudinality with ≥3 measurements to model temporal dynamics (changes in centrality and transfer between modules); Quasi-experiments with dosage measurement and fidelity to the Singapore model, linking exposure intensity and magnitude of structural rearrangement.

Analytical integration of psychometric networks + SEM with bootstrap for indirect routes, and explorations with machine learning (e.g., Random Forest) for nonlinearities and higher-order interactions; and Generalization across diverse cultural and linguistic contexts, with attention to specific dyslexia profiles and proportional reasoning, and the role of RAN in different orthographies.

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