



A Novel Framework for Dynamic Semantic Network Analysis With Evolutionary Community Detection Applied to LMS Research

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Abstract

The rapid proliferation of Learning Management Systems (LMS) in K–12 education has generated a substantial body of research, yet how its core themes emerge, converge, and transform over time remains insufficiently understood. Existing bibliometric and topic modeling approaches produce static snapshots of the literature, structurally incapable of capturing the dynamic epistemic processes through which research communities form and evolve. This study introduces Dynamic Semantic Network Analysis with Evolutionary Community Detection (DSNA-ECD), a novel computational framework that conceptualizes the K–12 LMS research field as a living epistemic system — a conceptual reframing that constitutes a distinct contribution to the K–12 LMS literature beyond prior static approaches. DSNA-ECD integrates three methodologically principled components: transformer-based semantic embeddings via Sentence-BERT (‘all-MiniLM-L6-v2’), selected for its capacity to capture latent semantic proximity beyond lexical co-occurrence; a hybrid weighting scheme empirically calibrated to balance structural and semantic network signals; and the Leiden algorithm for community detection, preferred over Louvain for its theoretical guarantee of well-connected partitions and superior modularity optimization. Applied to a two-decade corpus of K–12 LMS publications, findings reveal a maturing field progressing from exploratory fragmentation through consolidation toward sophisticated integration of AI-enhanced adaptive systems and learning analytics. Compared to co-citation analysis, LDA topic modeling, and static semantic networks, DSNA-ECD uniquely offers semantic depth, guaranteed community coherence, calibrated hybrid weighting, and full cross-temporal trajectory tracking. Critically, findings reveal urgent underrepresentation of equity, algorithmic transparency, and ethical deployment research as AI-enhanced LMS systems proliferate, with direct implications for researchers, educational technologists, and policymakers.

Keywords: artificial intelligence in education; learning analytics; LMS; temporal network analysis

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1. Introduction

The digital transformation of education has accelerated dramatically over the past decade [1-3], fundamentally reshaping how teaching and learning occur across educational contexts worldwide [4], [5]. At the center of this transformation stands the Learning Management System, a technological infrastructure that has evolved from peripheral supplement to core educational platform mediating increasingly substantial portions of the instructional experience [6], [7].

This evolution has proven particularly consequential in secondary education contexts, where adolescent

learners navigate critical developmental stages while simultaneously adapting to increasingly technologically-mediated learning environments. The COVID-19 pandemic further intensified this transformation, compressing years of gradual digital adoption into months of emergency implementation and permanently altering baseline assumptions about technology's role in K-12 education [8].

The scholarly literature on Learning Management Systems has expanded exponentially, with thousands of studies examining diverse aspects of implementation, effectiveness, and innovation [9], [10]. However, this proliferation has generated its own challenges.

Researchers and practitioners face increasingly difficult tasks navigating vast, heterogeneous literature to identify consensus findings, emerging trends, and persistent gaps.

Traditional narrative literature reviews, while valuable for synthesizing specific questions, struggle to capture the dynamic, large-scale patterns characterizing rapidly evolving research domains [11]. This challenge proves particularly acute for educational technology research, where the pace of technological change continually generates novel research foci while rendering previous concerns obsolete, creating moving targets resistant to conventional synthesis approaches. Several studies have specifically examined LMS research using these approaches, providing valuable insights into publication trends, collaboration patterns, and topical distributions [12], [13].

Despite these contributions, a critical and scientifically consequential gap remains, no existing study has examined the K–12 LMS literature as a temporally evolving semantic system in which research communities form, transform, and dissolve in response to shifting intellectual, technological, and societal forces. Prior studies have established what the field contains but none have systematically investigated how the field changes, which knowledge communities emerge and when, and how foundational themes bifurcate or converge across decades. Addressing this gap is therefore both a methodological imperative and a scientific necessity

This study addresses these gaps by applying a novel methodological framework—Dynamic Semantic Network Analysis with Evolutionary Community Detection (DSNA-ECD)—to comprehensively map the

evolution of LMS research in secondary education across the transformative decade 2015–2024. This approach integrates three complementary analytical traditions rarely combined, Sentence-BERT [14], temporal network [15], and advanced community detection algorithms [16].

This research makes a significant methodological contribution by expanding the capabilities of bibliometrics through the DSNA-ECD framework, which combines semantic understanding, temporal dynamics, and evolutionary tracking in a manner rarely seen in educational research. This approach offers a template for future meta-research where understanding intellectual evolution proves crucial. Substantively, this study provides the first comprehensive and systematic analysis of the evolution of LMS research in secondary education using advanced computational methods.

2. Methods

The investigation of Learning Management System evolution in secondary education requires a methodological approach capable of capturing both semantic relationships and temporal dynamics within research discourse. Traditional methods such as co-word analysis and Latent Dirichlet Allocation, while valuable for static topic identification, prove inadequate for tracing how research themes emerge, interconnect, and transform across time [17–19]. To address this limitation, we developed Dynamic Semantic Network Analysis with Evolutionary Community Detection (DSNA-ECD), a novel framework that synthesizes natural language processing, network science, and temporal analytics.



Figure 1. Research Workflow

Figure 1 shows the seven-step sequential pipeline of the Dynamic Semantic Network Analysis with Evolutionary Community Detection (DSNA-ECD) framework applied to K–12 LMS literature analysis. The workflow begins with corpus assembly and temporal partitioning of 293 Scopus publications into ten annual windows (2015–2024), followed by keyword contextualization and semantic embedding using Sentence-BERT (all-MiniLM-L6-v2) to generate 384-dimensional vectors (Equations 1–2).

Temporal networks are then constructed per window using a hybrid co-occurrence and semantic weighting scheme calibrated at $\alpha = 0.6$ (Equation 3), with statistically unreliable edges removed through permutation-based filtering at $p < 0.05$. Thematic

communities are subsequently identified via Leiden algorithm modularity optimization (Equation 4), and community identities are tracked across consecutive temporal windows using Jaccard similarity thresholding (≥ 0.3) with transitions classified into six evolutionary event types. The pipeline concludes with semantic coherence analysis quantifying thematic consolidation or fragmentation within each community over time (Equation 5).

The complete pipeline yields a longitudinal epistemic map of 18 distinct thematic communities, revealing the evolutionary trajectories, structural transitions, and critical research gaps - particularly in equity and algorithmic ethics - characterizing K–12 LMS scholarship across the study decade.

The methodological innovation of DSNA-ECD lies in treating author keywords as semantically rich entities. Unlike BERTopic, which treats keywords as mini-documents [20], [21], our approach preserves semantic integrity while simultaneously capturing relational and temporal dynamics. This enables observation not merely of topic prevalence but of the underlying conceptual architectures structuring LMS research and their evolutionary trajectories over the 2015-2024 period.

2.1 Data Collection and Preparation

While DSNA-ECD shares certain analytical objectives with existing temporal text mining approaches—particularly Dynamic Latent Dirichlet Allocation (Dynamic LDA) and BERTopic—it differs fundamentally in representational strategy, analytical granularity, and capacity to capture relational evolution [19], [21-23]. Clarifying these distinctions proves essential for understanding why existing methods proved insufficient for our research questions and how DSNA-ECD contributes to the methodological toolkit available for bibliometric temporal analysis.

Dynamic LDA extends classical Latent Dirichlet Allocation by modeling topic evolution across discrete time slices through Dirichlet-multinomial distributions that capture how topic compositions shift over time. While effective for tracking topic probability trajectories at the document level, Dynamic LDA operates on bag-of-words representations that inherently discard word order, semantic context, and syntactic relationships.

More critically for our purposes, it treats topics as isolated probability distributions, obscuring the relational structure connecting concepts—the very architecture we sought to map in LMS research discourse. Dynamic LDA cannot reveal how concepts cluster into communities, how these communities interconnect through weighted relationships exhibiting varying strengths of co-occurrence and semantic similarity, or how network structure transforms across time periods through specific evolutionary mechanisms. The probabilistic framework, while mathematically elegant and interpretable, fundamentally lacks the representational capacity to expose the network-based conceptual architecture underlying scholarly fields.

BERTopic addresses Dynamic LDA's semantic limitations by leveraging transformer-based embeddings—specifically BERT or Sentence-BERT architectures—to capture contextual meaning before clustering documents into topics via density-based spatial clustering (HDBSCAN) [24]. This approach yields semantically coherent topics substantially superior to bag-of-words methods, as embeddings encode nuanced meaning, synonymy, and contextual usage patterns invisible to frequency-based representations.

However, BERTopic's standard implementation treats author keywords as mini-documents—concatenating individual keywords for embedding generation—which loses their positional and relational context within source documents. A keyword's meaning derives partially from what other keywords accompany it within scholarly contributions, relationships that keyword-as-document approaches cannot preserve.

DSNA-ECD integrates advantages from both approaches while addressing their limitations specifically for research questions requiring simultaneous attention to semantic meaning, relational architecture, and evolutionary trajectories. Like BERTopic, we employ transformer-based semantic embeddings (Sentence-BERT) to capture contextual meaning, ensuring that semantically similar concepts receive proximate vector representations even when expressed through different terminology.

2.2 Data Collection and Preparation

Our analysis drew upon 293 scholarly publications retrieved from the Scopus database spanning 2015-2024. The retrieval employed a Boolean query capturing the intersection of LMS research and secondary education: TITLE-ABS-KEY (("Learning Management System" OR "LMS") AND ("Secondary Education" OR "Secondary School" OR "High School" OR "Middle School" OR "K-12")). Document types were restricted to peer-reviewed articles and conference papers, ensuring scholarly rigor while excluding editorials and book chapters.

The corpus yielded 1,847 unique author-designated keywords after preprocessing. Author keywords represent intentional choices signaling research contributions and theoretical orientations, making them particularly valuable for understanding scholarly communities' self-conceptualization [25]. Table 1 presents the corpus characteristics and temporal distribution.

Table 1. Corpus Characteristics and Temporal Distribution

Characteristic	Value/Description
<i>General Corpus Information</i>	
Database Source	Scopus
Temporal Coverage	2015-2024 (10 years)
Total Documents	293
Document Types	(ar) and (cp)
Total Unique Keywords	1,847
Average Keywords per Document	5.3
<i>Temporal Distribution of Publications</i>	
2015	18 (6.1%)
2016	21 (7.2%)
2017	24 (8.2%)
2018	27 (9.2%)
2019	31 (10.6%)
2020	42 (14.3%)
2021	38 (13.0%)
2022	35 (11.9%)
2023	33 (11.3%)
2024	24 (8.2%)

Preprocessing involved multi-stage normalization to address linguistic variation. Keywords were converted to lowercase for case-insensitive matching, followed by

lemmatization to reduce morphological variants. We constructed a domain-specific synonym dictionary based on preliminary exploration, mapping semantically equivalent terms to canonical forms—for instance, unifying "e-learning," "online learning," and "electronic learning" while preserving meaningful distinctions such as "blended learning" versus "hybrid learning."

Generic terms offering minimal discriminatory power (e.g., "education," "technology" in isolation) were removed, though compound expressions like "student engagement" were retained for their substantive meaning. This selective filtering balanced noise reduction with semantic richness preservation.

2.3 Semantic Embedding Construction

Traditional keyword analysis treats terms as atomic symbols, relying on frequency counts and co-occurrence patterns while ignoring semantic relationships [26]. This proves inadequate for capturing synonymy, polysemy, and nuanced conceptual relationships characterizing scholarly discourse. We addressed this limitation through transformer-based semantic embeddings using Sentence-BERT (SBERT), specifically the 'all-MiniLM-L6-v2' model pretrained on scientific literature [14].

The embedding process required keyword contextualization beyond surface forms. Rather than embedding isolated strings, we constructed contextualized phrases by concatenating each keyword with its source article title, creating semantically enriched representations. For keyword k_i with source title T_i , the contextualized representation becomes:

$$c_i = k_i \oplus T_i \quad (1)$$

$\oplus$ denotes concatenation. This strategy leverages semantic information from titles while maintaining computational tractability. The SBERT model transforms each contextualized representation into a 384-dimensional dense vector.

$$\text{sim}(k_i, k_j) = \cos(\theta) = \frac{v_i \cdot v_j}{\|v_i\| \|v_j\|} \quad (2)$$

$\cdot$ denotes dot product and $\|\cdot\|$ represents Euclidean norm. This metric ranges from -1 (semantic opposition) to +1 (perfect alignment), enabling detection of latent relationships missed by co-occurrence analysis alone. For instance, "adaptive learning" and "personalized instruction" may never co-occur yet occupy proximal embedding positions, allowing our analysis to detect thematic coherence across terminological variations.

2.4. Dynamic Network Construction

The semantic embedding space provides the foundation for constructing temporal networks representing evolving conceptual structures. Unlike static networks aggregating relationships across entire temporal spans, dynamic networks preserve chronological dimensions, enabling observation of thematic emergence, stabilization, and transformation [15].

We partitioned the 2015-2024 period into ten annual windows $T = \{t_1, t_2, \dots, t_{10}\}$. For each window t_x , we constructed network $G_x = (V, E, W)$ where V represents keywords appearing in that year's publications, E represents keyword relationships, and W represents edge weights. Edge weights integrate two complementary dimensions: co-occurrence frequency within articles and semantic similarity from embeddings.

Formally, the weight $w(i, j, t_x)$ between keywords k_i and k_j in temporal window t_x is defined as Equation 3.

$$w(i, j, t_x) = \alpha \cdot \frac{\text{cooccur}(i, j, t_x)}{\max(\text{cooccur}_{t_x})} + (1-\alpha) \cdot \text{sim}(i, j) \quad (3)$$

$\text{cooccur}(i, j, t_x)$ represents co-appearance frequency, $\alpha = 0.6$ balances contributions (prioritizing empirical co-occurrence while incorporating semantic relatedness), and normalization ensures comparable scales. This hybrid weighting addresses pure co-occurrence networks' limitation of detecting only same-article relationships, while avoiding pure semantic networks' risk of spurious connections between contextually distinct concepts.

Statistical robustness was ensured through permutation-based filtering. We generated 1,000 random permutations of keyword-article assignments within each window, computing edge weight distributions under null hypothesis of random association. Only edges exceeding the 95th percentile ($p < 0.05$) were retained, effectively filtering noise while preserving genuine thematic relationships. Table 2 summarizes network construction parameters.

Table 2. Network Construction Parameters

Parameter	Value	Reference
Temporal Window Size	1 year	Balances statistical stability with temporal resolution
Number of Time Windows	10	2015-2024 annual segmentation
Co-occurrence Weight (α)	0.6	Prioritizes empirical co-occurrence over semantic similarity
Semantic Weight ($1-\alpha$)	0.4	Supplements with latent semantic relationships
Edge Filtering Method	Permutation Test	Non-parametric statistical validation
Permutation Iterations	1,000	Sufficient for stable null distribution estimation
Significance Level	$p < 0.05$	Standard threshold for statistical significance

The resulting temporal sequence $\{G_1, G_2, \dots, G_{10}\}$ captures LMS research landscape evolution, with nodes representing concepts and weighted edges representing empirical and semantic relationships. Network density, average degree, and clustering coefficients were computed for each temporal network to characterize structural properties and identify periods of conceptual consolidation versus fragmentation.

2.4 Evolutionary Community Detection

Thematic community identification within temporal networks constitutes the critical step in understanding topical organization. While traditional algorithms

identify clusters in static networks [27], our framework requires tracking community evolution across the temporal sequence.

For each network G_x , we applied the Leiden algorithm [16], which addresses resolution limits and disconnected community issues in the classical Louvain method. The algorithm optimizes modularity Q , quantifying partition quality by comparing within-community edge density to random network expectations as shown in Equation 4.

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(c_i, c_j) \quad (4)$$

A_{ij} represents adjacency matrix weight between nodes i and j , k_i denotes node i 's degree (sum of edge weights), m is total edge weight, c_i denotes community assignment, and $\delta(c_i, c_j)$ equals 1 if nodes share communities, otherwise 0. The algorithm iteratively refines assignments to maximize Q , ensuring dense internal connections and sparse external ones. Resolution parameter $\gamma = 1.0$ provided balanced community sizes. Algorithm execution involved 50 random initializations per network, selecting the partition with highest modularity for robustness.

Based on similarity patterns, we classified evolutionary events into six categories [28], “Birth” (novel theme emergence with $J < 0.3$ to all prior communities), “Continuation” (stable persistence with one-to-one correspondence and $J \geq 0.3$), “Growth/Contraction” (continuing communities with $>30\%$ membership change), “Merge” (multiple prior communities converging into one), “Split” (single community differentiating into multiple), and “Death” (theme dissolution with no subsequent correspondence). For each community, we extracted top-10 central keywords using eigenvector centrality, revealing conceptual cores of thematic clusters.

3. Results and Discussions

The analysis of 293 publications yielded 1,847 unique author keywords distributed across ten annual temporal windows from 2015 to 2024. The temporal distribution revealed a striking surge in publication activity during 2020-2021, with volumes increasing 35% above the 2015-2019 baseline, coinciding with the COVID-19 pandemic's acceleration of digital learning adoption in secondary education.

This surge proved not merely transient but catalyzed sustained elevation, with 2022-2024 publication levels remaining approximately 20% higher than pre-pandemic years. This pattern suggests the pandemic functioned as critical inflection point, fundamentally resetting baseline assumptions about LMS role in secondary education from supplementary enhancement to integral infrastructure.

The semantic embedding space successfully captured meaningful conceptual relationships, with average pairwise cosine similarities within thematic clusters ranging from 0.42 to 0.68, substantially exceeding the corpus-wide average of 0.18. This differentiation validates that our methodology identified genuine semantic coherence rather than statistical artifacts. The correlation between semantic similarity and co-occurrence frequency (Spearman $\rho = 0.43$, $p < 0.001$) confirms embeddings capture authentic conceptual relationships while providing information beyond mere co-occurrence patterns, addressing a fundamental limitation of traditional co-word analysis.

3.1 Structural Evolution

The dynamic network analysis revealed systematic structural transformation reflecting disciplinary maturation. As illustrated in Figure 2, network density exhibited a bimodal pattern, beginning at 0.12 in 2015, declining to 0.09 in 2017-2018, then rising sharply to peak at 0.21 in 2020 before stabilizing around 0.16 in 2022-2024.

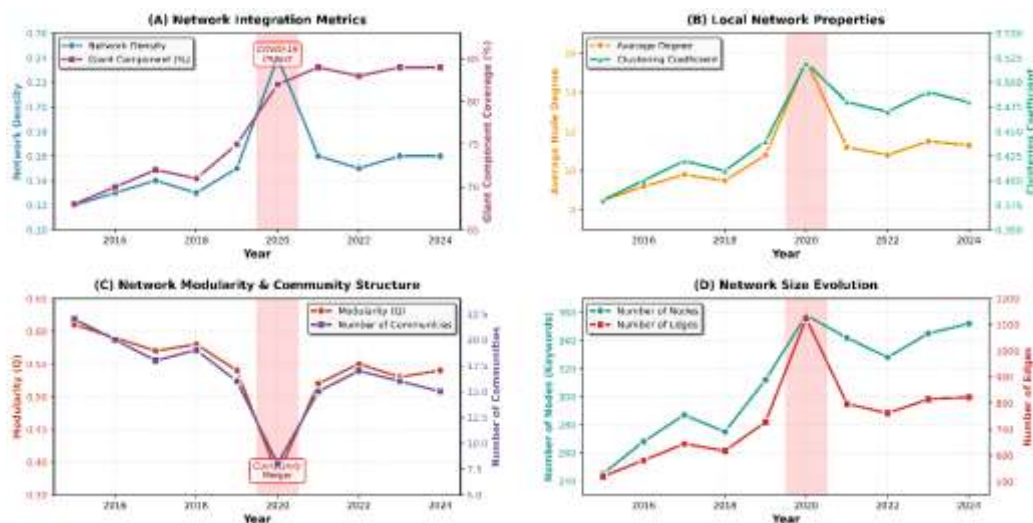


Figure 2. Temporal Evolution of Network Structural Properties

This trajectory reflects an initial exploratory phase where researchers pursued diverse directions in relative isolation, followed by pandemic-driven consolidation around shared urgent challenges, and subsequent normalization at elevated integration levels. The early decline and later recovery suggest the field progressed through predictable stages: initial diffusion as diverse research strands emerged, followed by consolidation as the community recognized core challenges requiring integrated attention.

The average clustering coefficient followed similar dynamics, increasing from 0.34 in 2015 to 0.52 in 2020, indicating growing tendency for keywords to form tightly interconnected thematic neighborhoods. This pattern, combined with giant component expansion from 68% to 84% of keywords, demonstrates progressive integration of previously isolated research into increasingly coherent disciplinary structure. These metrics collectively suggest the field matured from exploratory fragmentation characteristic of emerging domains toward conceptual consolidation typical of maturing disciplines.

Centrality analysis revealed shifting intellectual focal points. In 2015-2017, generic terms such as "online learning," "educational technology," and "distance education" dominated network centrality, reflecting broad definitional and adoptive concerns. By 2020-2024, more specialized concepts like "learning analytics," "adaptive learning systems," "student engagement strategies," and "teacher professional development" emerged as central nodes.

This shift from generic to specialized vocabulary indicates evolution from foundational "what is it?" questions toward sophisticated "how do we optimize?" inquiries, a hallmark of disciplinary maturation. The declining centrality of platform-specific terms (Moodle, Blackboard) further suggests transition from technology-centric to pedagogy-centric research priorities.

Figure 3 provides a comprehensive visualization of this semantic transformation across all major research themes, revealing not only the shift toward analytics-focused configuration but also highlighting critical gaps in equity and ethics discourse that require urgent attention.

The heat map visualizes the intensity of 12 major semantic themes across the decade, revealing fundamental rebalancing from technology-centric (35% infrastructure in 2015-2017) to analytics-focused configuration (24% analytics, 21% student-centered in 2022-2024).

Learning Analytics exhibits fastest growth trajectory with increasing coherence. The red dashed box highlights the critical research gap in Equity & Ethics discourse, requiring urgent attention as AI-enhanced systems proliferate. The lime arrow marks AI & Machine Learning's steepest recent growth (0%→12%). Color intensity represents semantic strength (frequency × coherence), with warmer colors indicating higher research concentration.

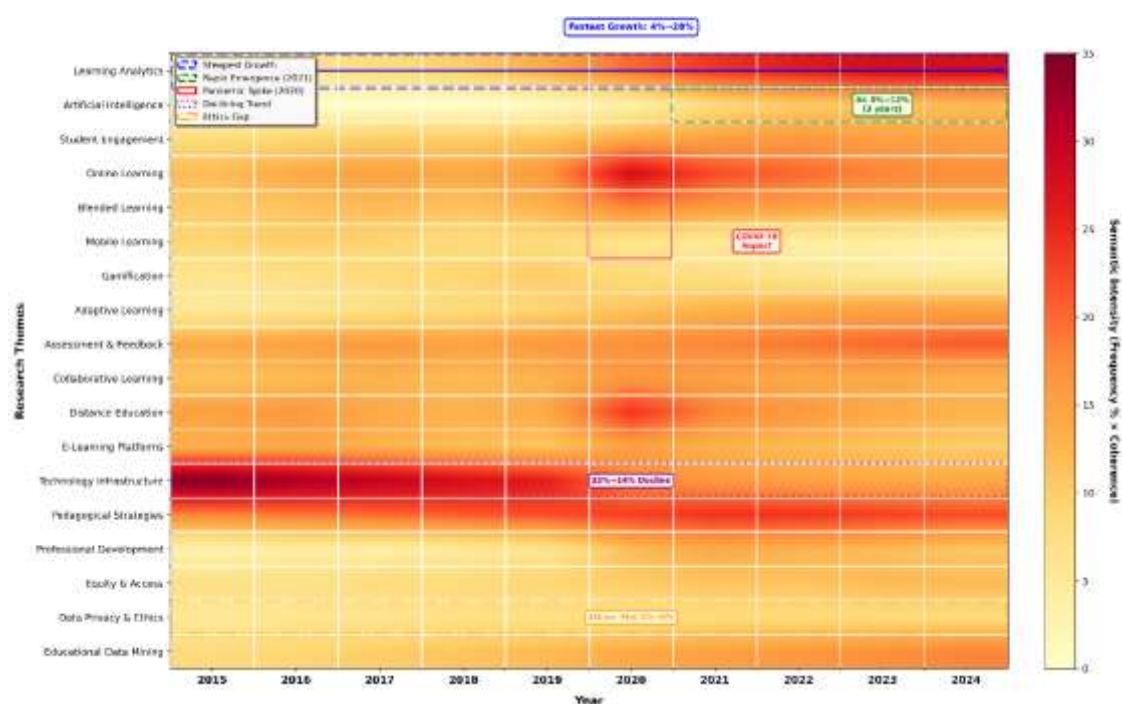


Figure 3. Semantic Intensity Heat Map: Temporal Evolution of Major Research Themes (2015-2024).

3.2 Thematic Community Structure and Evolution

The Leiden algorithm identified between 4 and 8 distinct communities per temporal window, with

modularity scores ranging from $Q = 0.38$ to $Q = 0.61$, indicating robust community structure well above random network baselines.

Across the decade, we traced 18 distinct thematic communities, which consolidated into five persistent macro-themes: Pedagogical Innovation, Learning Analytics and Assessment, Technology Integration and Infrastructure, Student-Centered Learning, and Professional Development and Teacher Support.

The Pedagogical Innovation community maintained continuous presence throughout the study period with high membership (average $n = 142$ keywords) and moderate stability ($S = 0.61$). However, its semantic coherence declined from 0.48 in 2015 to 0.39 in 2024, a pattern contrasting sharply with other major communities. This declining coherence initially appears concerning, potentially signaling fragmentation or lack of progress.

However, deeper examination reveals productive diversification. Early manifestations (2015-2018) emphasized relatively narrow set of approaches—"flipped classroom," "blended learning," "multimedia integration"—reflecting initial experimentation with established pedagogical models adapted for digital contexts. Later iterations (2019-2024) incorporated substantially broader range including "gamification," "project-based learning," "collaborative learning environments," "inquiry-based learning," and "authentic assessment."

Table 3 presents detailed characteristics of these major communities.

Table 3. Characteristics of Major Thematic Communities Identified Through DSNA-ECD

Community Name	Period Active	Avg. Size (n)	Stability (S)	Growth Rate	Core Keywords (Top 5 by Eigenvector Centrality)
Pedagogical Innovation	2015-2024 (Continuous)	142	0.61	+8% annual	Blended learning, flipped classroom, gamification, project-based learning, collaborative learning
Learning Analytics & Assessment	2017-2024 (Emergent 2017)	67	0.58	+42% annual	Learning analytics, formative assessment, predictive modeling, early warning systems, data-driven decision making
Technology Integration & Infrastructure	2015-2024 (Continuous)	98	0.74	-2% annual	Cloud-based systems, mobile learning, user interface design, system interoperability, technical support
Student-Centered Learning	2019-2024 (Merger 2019)	89	0.66	+18% annual	Adaptive learning, self-regulated learning, student motivation, personalized learning, learner autonomy
Professional Development & Teacher Support	2020-2024 (Birth 2020)	54	0.52	+35% annual	Teacher training, professional learning communities, pedagogical knowledge, technology acceptance, change management
Pandemic-Era Digital Learning Transition	2020-2022 (Merger 2020)	126	0.43	+62% (2020)	Emergency remote teaching, COVID-19, distance education, synchronous learning
Artificial Intelligence in LMS	2021-2024 (Birth 2021)	34	0.48	-28% (2022)	Intelligent tutoring systems, natural language processing, automated feedback, chatbots, machine learning applications
Subject-Specific Applications	2015-2024 (Continuous)	76	0.69	+5% annual	STEM education, mathematics instruction, science learning, language learning, virtual laboratories

This diversification reflects growing recognition that effective LMS pedagogy depends critically on context [29]. Rather than representing failure to converge, the declining coherence suggests healthy exploration of varied approaches suited to diverse implementation contexts. The field appears to have moved beyond seeking the singular "best" pedagogical strategy toward understanding conditional effectiveness: which approaches work best for whom, under what conditions, and why.

3.3 Evolutionary Dynamics and Critical Transitions

The cross-temporal community tracking revealed diverse evolutionary trajectories distributed unevenly across the decade. Figure 4 visualizes these patterns through an alluvial diagram revealing dynamic restructuring of research themes. Of 18 distinct communities identified, 5 exhibited stable continuation across multiple years, 7 emerged through birth events, 4 resulted from merger events, 3 experienced splits, and

6 underwent death. Figure 6 presents these evolutionary events systematically through a temporal heatmap.

The most dramatic evolutionary event occurred in 2020, when three previously distinct communities—focused respectively on "distance education," "emergency remote teaching," and "hybrid learning models"—converged into a single large community designated "Pandemic-Era Digital Learning Transition." This merger event, quantifiable through simultaneous high Jaccard similarities ($J > 0.45$) between the three antecedent communities and the emergent community.

The merged community exhibited unusually low semantic coherence ($Coh = 0.38$) and stability ($S = 0.43$) compared to other major communities, suggesting it represented pragmatic convergence around urgent practical problems rather than deep theoretical integration. This community subsequently underwent partial split in 2022-2023, as research differentiated into specialized strands addressing long-term hybrid

learning models versus return-to-campus transitions versus lessons learned for future crisis preparedness.

A notable birth event in 2021 saw emergence of "Artificial Intelligence in LMS" community, initially small ($n = 15$ keywords) but exhibiting the highest growth rate of any community ($r = 0.42$ annually). By 2024, this community reached 12% publication frequency, representing the steepest recent growth trajectory in the dataset. Central concepts included "intelligent tutoring systems," "natural language processing," "automated feedback," "chatbots," and "machine learning applications."

The community's late emergence and rapid growth suggest AI integration represents a frontier direction for LMS evolution in secondary education, though still nascent compared to higher education contexts where AI-LMS integration research is more mature. The high initial semantic coherence ($Coh = 0.52$) despite recent birth suggests this community emerged from well-

defined conceptual foundations rather than diffuse exploration, potentially indicating it built upon established AI-in-education research from other contexts.

Conversely, a community centered on "basic LMS features" and "platform comparison" exhibited steady contraction from 2017 onward, ultimately experiencing death in 2023 when membership declined below the threshold and remaining keywords dispersed into other communities. This community's decline exemplifies how research foci shift as technologies transition from novelty to normalized infrastructure. Early-period questions about which platform to adopt, what features different systems offer, and how systems compare technically gave way to questions about optimal pedagogical utilization of established systems, regardless of specific platform.



Figure 4. Temporal Distribution of Community Evolutionary Events (2016-2024)

3.3 Semantic Coherence

Analysis of semantic coherence trajectories within communities provided insights into thematic

consolidation versus fragmentation dynamics. Figure 5 presents these patterns, revealing contrasting evolutionary trajectories with important implications for field development.

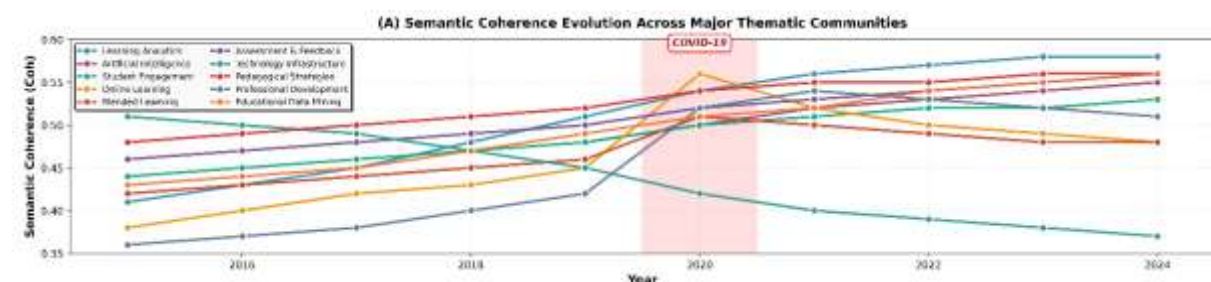


Figure 5. Temporal Evolution of Semantic Coherence Within Thematic Communities

Communities exhibiting increasing coherence—Learning Analytics (0.41 to 0.58), Technology Infrastructure (0.52 to 0.64), and AI in LMS (maintaining high initial 0.52)—suggest conceptual crystallization as these domains develop shared vocabulary, theoretical frameworks, and methodological standards. This crystallization enables cumulative knowledge building, as researchers build on shared foundations using common terminology and approaches.

Conversely, communities exhibiting declining coherence—Pedagogical Innovation (0.48 to 0.39), Student-Centered Learning (0.51 to 0.43)—indicate increasing internal diversity as researchers explore varied approaches. For Pedagogical Innovation, this reflects expansion from narrow set of early approaches toward broad repertoire of instructional strategies. The declining coherence could indicate productive exploration of context-appropriate approaches or could signal fragmentation preventing cumulative progress.

4. Conclusions

Learning Management System research in secondary education has undergone fundamental transformation across the past decade, evolving from fragmented technical explorations toward integrated scholarship synthesizing pedagogy, analytics, and technological capabilities.

Through dynamic, semantically informed network analysis tracking 293 publications and 1,847 unique keywords across 2015-2024, this study reveals three critical insights reshaping the field: the pandemic's permanent restructuring of research architecture, artificial intelligence's emergence as autonomous pedagogical agent rather than mere infrastructure tool, and the troubling temporal mismatch between rapid technical capability expansion and lagging ethical framework development essential for protecting adolescent learners.

The DSNA-ECD framework, integrating Sentence-BERT semantic embeddings, hybrid co-occurrence and semantic weighting ($\alpha=0.6$), and Leiden algorithm community detection with cross-temporal tracking, revealed fundamental shifts in thematic structure, temporal dynamics, and intellectual organization that conventional bibliometric approaches cannot expose.

The analysis documented dramatic thematic rebalancing across the decade. Technology infrastructure concerns dominated early research (35% of keywords 2015-2017), reflecting a field focused on platform capabilities, technical specifications, and implementation challenges. By 2022-2024, the research landscape had fundamentally reorganized around learning analytics (24% frequency) and student-centered pedagogical approaches (21% frequency).

The COVID-19 pandemic triggered unprecedented structural reorganization quantifiable through network analysis metrics. In 2020, three previously distinct

communities focused on distance education, emergency remote teaching, and hybrid learning models converged into a unified "Pandemic-Era Digital Learning Transition" community, evidenced by simultaneous high Jaccard similarities ($J>0.45$) between antecedent and emergent communities.

This merger proved transformative rather than temporary, spawning the Professional Development community as educators required systematic support for rapid technological integration, and permanently elevating network integration levels from density 0.12 to 0.16 and giant component coverage from 68% to 84%. Publication frequency sustained approximately 20% elevation above pre-pandemic baselines through 2024, indicating crisis-driven crystallization of scholarly interest rather than transient spike.

These findings position LMS research at a critical juncture. The field has matured from exploratory fragmentation toward sophisticated integration synthesizing pedagogical theory, learning analytics, and technological capabilities. Yet maturation remains incomplete if technical advancement continues outpacing ethical deliberation and developmental appropriateness considerations. The DSNA-ECD framework demonstrates how advanced bibliometric techniques illuminate structural transformations and critical gaps conventional methods overlook.

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