Review Article

Cognitive Load in the Age of Artificial Intelligence: A Bibliometric Analysis (2021–2025)

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Abstract

Background: The integration of AI and digital learning technologies has transformed education but introduced cognitive overload challenges. Cognitive Load Theory (CLT) offers a framework for understanding information processing in technology-enhanced environments, yet its intellectual structure in the post-pandemic AI-driven landscape remains underexplored.
Summary: This bibliometric analysis of 1,600 open-access CLT publications (2021-2025) from HYPERLINK "https://dimensions.ai/"Dimensions.ai examined publication trends, citation impact, collaboration patterns, and thematic clusters using VOSviewer. Results show 28% annual growth. Three clusters dominate (74% link strength): (a) Educational and Developmental Psychology (motivation, resilience, schema construction); (b) Clinical and Cognitive Sciences (cognitive interventions, well-being); and (c) Information and Computing in Human-centred Contexts (AI-driven adaptive learning). The USA, Australia, and UK lead in impact; Asia-Pacific (China, Singapore, Hong Kong) emerges as a technology-focused hub. Education and Information Technologies showed the highest mean citation rate.
Key Message: This first bibliometric review maps CLT's post-2020 evolution toward human-AI symbiosis, providing an empirical framework for cognitively sustainable digital learning environments and confirming CLT's growing interdisciplinary integration with educational technology and cognitive science.

Keywords

Cognitive Load Theory, bibliometric analysis, educational technology, research trends, digital learning

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Introduction

The twenty-first century has witnessed an unprecedented transformation in educational systems through the integration of digital technologies, artificial intelligence (AI) and multimedia-based learning environments. This transformation has not only changed how learners acquire knowledge but also how teachers design, deliver and assess instruction.[1] While these advancements promise personalised learning, improved engagement and global access to education, they simultaneously present a significant challenge: the risk of cognitive overload among learners.[2] As digital platforms become richer in content and more interactive, students are often required to process vast quantities of information in limited cognitive time frames.[3] This complexity forms the genesis of the present study, emphasising the urgent need to understand how Cognitive Load Theory (CLT) has evolved and been applied to manage cognitive processes effectively in the age of technological immersion.

In earlier decades, traditional classroom instruction relied primarily on linear, teacher-centred approaches. The flow of information was relatively controlled, and learners engaged in predictable patterns of cognitive activity. However, the emergence of technology-enhanced learning environments, including e-learning platforms, gamified systems, virtual laboratories and adaptive AI tutors, has revolutionised both teaching and learning processes.[4] Students now engage with

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multiple modalities simultaneously: text, audio, video, animation, simulation and interactive feedback. This multiplicity, while pedagogically enriching, can impose high cognitive demands, especially when instructional design does not align with how the human brain processes information.[5]

Educational psychologists began to observe that, despite the availability of advanced technologies, learning outcomes did not always improve proportionally. In some instances, learners exhibited reduced comprehension, fragmented attention or cognitive fatigue, symptoms indicative of cognitive overload.[6] This discrepancy highlights the need to investigate the mechanisms by which learners process information and the instructional conditions that optimise cognitive efficiency.[7] Hence, CLT, developed by John Sweller (1988), emerged as a powerful explanatory and prescriptive framework for designing effective instruction.

CLT is grounded in the information processing model of human cognition, which posits that learning involves transferring information from working memory to long-term memory through the formation and automation of schemas.[8] Since working memory has limited capacity and duration, effective instructional design must minimise unnecessary mental effort and maximise schema construction. CLT identifies three primary types of cognitive load:

The Classic Triad: Intrinsic, Extraneous and Germane Load

1. Intrinsic load: The inherent complexity of the material is determined by the number of interacting elements that must be processed simultaneously.
2. Extraneous load: The mental effort imposed by poor instructional design or irrelevant task features that distract from the learning goal.
3. Germane load: The cognitive resources devoted to processing, constructing and automating schemas necessary for long-term learning.

An optimal instructional design aims to reduce extraneous load, manage intrinsic load and enhance germane load. When this balance is achieved, learners are more capable of meaningful engagement and long-term knowledge retention.[9] In the digital era, however, achieving such an equilibrium has become increasingly challenging. Multimedia materials, hyperlinked interfaces and simultaneous channels of information can overwhelm learners, reducing cognitive efficiency.[10] Thus, understanding and applying CLT principles have become essential for the development of effective *techno-pedagogical* practices.

As education systems have shifted towards *constructivist and learner-centred paradigms*, the role of CLT has expanded from a mere cognitive framework to a multidimensional tool guiding instructional innovation. In contemporary research, CLT intersects with diverse fields such as *AI in education (AIED)*, *neuroeducation*, *human–computer interaction* and *affective computing*. Scholars now explore how cognitive load interacts with emotional engagement, motivation and adaptive feedback mechanisms.[11] Moreover, the rise of AI-based personalised learning environments has prompted renewed inquiry into how algorithms can dynamically adjust instructional content to maintain an optimal cognitive load for each learner.[12]

This diversification of research has created an expansive and complex body of literature. While earlier studies focused primarily on classroom-based experiments and instructional design models, recent research has examined the integration of CLT principles into intelligent tutoring systems (ITS), augmented and virtual reality (AR/VR) learning spaces, and game-based learning frameworks.[13] Such diversity, while enriching, also generates fragmentation, making it difficult to identify core research directions, intellectual clusters and collaborative networks.[14] This fragmentation underscores the *need for a bibliometric synthesis* to map the intellectual landscape and evolution of CLT across disciplinary and geographical boundaries.

The significance of this study lies in the central role that CLT plays in shaping the design and evaluation of modern educational systems.[15] As digital transformation accelerates, understanding the cognitive architecture of learners becomes a foundational requirement for achieving meaningful learning outcomes. Poorly designed multimedia instruction can lead to *information overload*, *attention fatigue* and *reduced transfer of learning*, thereby undermining the potential of digital education.[16] By contrast, instructional environments grounded in CLT principles can foster *deep learning*, *motivation* and *academic resilience*, qualities essential for twenty-first-century learners.[17]

Beyond its pedagogical relevance, CLT serves as a bridge between cognitive psychology and emerging technologies. It provides a scientific basis for the design of *AI-based adaptive learning systems*, enabling personalised instruction that respects the limits of human cognition.[18] In this sense, CLT research contributes not only to educational theory but also to the broader fields of *cognitive computing*, *human-centred AI* and *learning analytics*.[19] Therefore, examining its bibliometric structure offers valuable insights into how interdisciplinary collaboration drives theoretical innovation and practical application.

Despite extensive CLT scholarship, comprehensive data-driven reviews mapping its intellectual structure remain scarce. Traditional qualitative reviews capture thematic content but overlook quantitative patterns, author influence, institutional productivity, thematic clustering and citation impact, which shape research trajectories. Consequently, scholars lack clarity regarding CLT's most influential areas, leading contributors and collaborative evolution.

This study addresses this gap through a bibliometric analysis of 1,600 open-access CLT publications (2021–2025) from Dimensions.ai. Using citation analysis, co-authorship networks and cluster mapping, it identifies prolific authors, institutions, countries and thematic intersections across psychology, education and computing sciences.

The significance is twofold. Academically, it clarifies intellectual evolution, guiding scholars towards underexplored areas and cross-disciplinary integration of cognitive, emotional and technological dimensions. Practically, it informs cognitively efficient digital learning design for educators and provides policymakers with empirical foundations for investing in cognitively aligned technologies.

Notably, prior comprehensive reviews[11] mapped CLT scholarship only through 2020, focusing on traditional multimedia and classroom contexts. These works preceded three transformative developments that have fundamentally reshaped the educational landscape: (a) the COVID-19 pandemic-driven shift to digital and blended learning, making cognitive load management a practical necessity; (b) the widespread deployment of AIED, including large language models, adaptive tutoring systems and learning analytics, enabling real-time cognitive load measurement and personalised instruction; and (c) the proliferation of immersive technologies (VR, AR, mixed reality) is introducing novel multimodal learning environments requiring re-examination of CLT principles.

These developments have generated a burgeoning body of post-2020 scholarship reflecting a qualitative shift towards interdisciplinary integration with computer science, neuroscience and human-centred computing, alongside evolving global collaboration patterns. This investigation addresses this critical gap by providing the first bibliometric synthesis of CLT research spanning the transformative 2021–2025 period, mapping its evolution from a foundational educational psychology framework to a multidisciplinary pillar supporting AI-enhanced, cognitively sustainable digital learning ecosystems.

Objective of the Problem

1. To analyse global publication trends and citation impact of CLT research from 2021 to 2025.
2. To identify leading authors, institutions, countries and journals shaping CLT scholarship.
3. To map key thematic clusters and interdisciplinary linkages through bibliometric and network analyses.
4. To examine global collaboration patterns and derive insights for cognitively sustainable digital learning practices.

Theoretical Background: The Foundations and Evolution of Cognitive Load Theory

To fully appreciate the contemporary intellectual structure of CLT mapped in this bibliometric review, it is essential to understand its theoretical foundations and key evolutionary milestones. CLT is not a monolithic theory but a dynamic framework that has evolved significantly since its inception, driven by empirical findings and the changing landscape of learning environments. The foundational principles of CLT are given below.

- Schema theory: This posits that knowledge is stored in long-term memory as cognitive constructs called 'schemas', which organise information and automate problem-solving procedures. Learning, therefore, is the process of acquiring and automating these schemas.
- The limited capacity of working memory: CLT emphasises that working memory, the cognitive system where conscious information processing occurs, is severely limited in both capacity and duration.

The central challenge of learning, as framed by CLT, is that novel information must be processed by a limited working memory before it can be stored in a virtually unlimited long-term memory. Effective instruction must, therefore, be designed to manage the load on working memory to facilitate schema acquisition.

Key Instructional Effects and Model Advancements

The predictive power of CLT is demonstrated through a series of well-researched instructional effects derived from its principles. These effects explain how to optimise the balance of cognitive load (Table 1).

Cognitive Load Theory in the Digital Age: A Necessary Framework

The principles and effects of CLT, initially developed in paper-based and traditional classroom settings, have proven even more critical in the context of digital and multimedia learning. It is from this rich theoretical and empirical foundation that CLT has expanded into its current, multidisciplinary form. The contemporary research landscape, which this study maps, represents the natural evolution of these core ideas as they intersect with new technologies, new learning domains and new methodological approaches. This bibliometric analysis, therefore, captures the living trajectory of a theory that has moved from explaining problem-solving in well-defined domains to guiding the design of cognitively efficient learning in an increasingly complex digital world.

Cognitive Load Theory and Artificial Intelligence-based Learning Environments

Recent advances in AI have accelerated the development of adaptive and ITS that explicitly aim to manage learners' cognitive load by adjusting task complexity, sequencing and feedback in real time.[20] By operationalising CLT principles, reducing extraneous load, managing intrinsic load through scaffolding, and supporting germane processing, AI systems can personalise instruction to a learner's current cognitive state and prior knowledge, thereby improving efficiency and learning gains.[21] Several recent systematic reviews and empirical studies report that AI-driven ITSs frequently incorporate CLT-based design choices (e.g., worked examples, stepwise problem decomposition and adaptive hints) and that, when well-designed,[22] these systems can reduce cognitive

Table 1. Key Instructional Effects and Model Advancements.

S. No.	Instructional Effect	Description
1	The goal-free effect	Using goal-free problems reduces the extraneous load associated with searching for a solution, allowing learners to focus on understanding the problem states and operators.
2	The worked-example effect	Studying worked examples is often more effective than solving equivalent problems, as it directly reduces extraneous load and demonstrates correct solution procedures, facilitating schema construction.
3	The modality effect	Presenting information in a mixed visual and auditory format (e.g., diagrams with spoken text) leverages both the visual and auditory channels of working memory, effectively expanding its functional capacity compared to using a single channel (e.g., diagrams with on-screen text).

burden and improve performance in domains such as programming and K-12 learning.

Concurrently, advances in physiological and interaction-based measurement (e.g., electroencephalography (EEG), functional near-infrared spectroscopy (fNIRS), eye-tracking and fine-grained log data) are enabling *cognitive-aware* AI: systems that infer cognitive load continuously and adapt content, pacing or modality accordingly. Recent proof-of-concept and applied studies demonstrate viable pipelines for real-time classification of workload (using fNIRS and machine learning) and for embedding those signals into adaptive loops that modify instructional support. This fusion of CLT and cognitive sensing opens possibilities for closed-loop tutoring (e.g., increasing worked-example usage when load is high; fading scaffolds as load normalises), but it also raises design and ethical questions about measurement validity, intrusiveness and equity.[23]

Despite promising results, the literature also highlights important caveats. Large recent reviews suggest that ITS effectiveness is heterogeneous, dependent on implementation fidelity, domain and the quality of learner models, and that some AI features (e.g., excessive automation or poor hint timing) can unintentionally increase extraneous load or foster cognitive offloading that undermines deeper learning. Thus, contemporary CLT scholarship advocates for careful co-design between learning scientists, AI engineers and educators to ensure that adaptive behaviours are pedagogically grounded and that systems measure *relevant* cognitive states rather than proxy signals.[24] Future research should prioritise (a) validating multimodal load measures across contexts, (b) transparency in adaptation rules, and (c) longitudinal studies that examine whether cognitive-aware AI fosters durable schema construction rather than short-term performance gains.

Methods

Research Approach

The present study employs a*quantitative bibliometric research design* to systematically analyse the intellectual structure, publication trends and collaboration networks within the field of CLT from 2021 to 2025. Bibliometric analysis, being both descriptive and inferential in nature, provides an empirical basis for evaluating the development of research domains through measurable indicators such as publication count, citation frequency, co-authorship strength and thematic clustering.

The study adopts a *Scientometric mapping approach*, which integrates statistical techniques and network visualisation tools to uncover structural patterns in academic literature. This design is particularly suitable for identifying emerging research themes, influential scholars and evolving trends within interdisciplinary fields such as educational psychology, instructional design and human–computer interaction. The overall research design and analytical framework are illustrated in Figure 1.

Data Source and Selection Criteria

The data set for this study was extracted from the Dimensions.ai database, a comprehensive, open-access scholarly index that includes publications, citations, grants, patents, clinical trials and policy documents. Dimensions.ai was selected for its wide coverage and inclusion of both open-access and peer-reviewed literature relevant to education, psychology and computing sciences. Figure 2 presents the search strategy and filtering procedure.

The filtering process, guided by the inclusion and exclusion criteria outlined in Table 2 and Table 3, yielded a final curated data set of 1,600 open-access publications specifically focused on CLT. Excluded records comprised non-peer-reviewed sources (conference proceedings, editorials and preprints), non-English publications, duplicates, works outside the specified time frame, and records with incomplete metadata. Additionally, data sets, grants, patents, clinical trials and policy documents were excluded to maintain a thematic focus on core research publications.

Following the selection of studies from the Dimensions.ai database, the raw bibliographic records were exported to comma-separated values and processed in Microsoft Excel for data cleaning and consistency verification. Duplicate entries were identified and removed using automated Excel macros

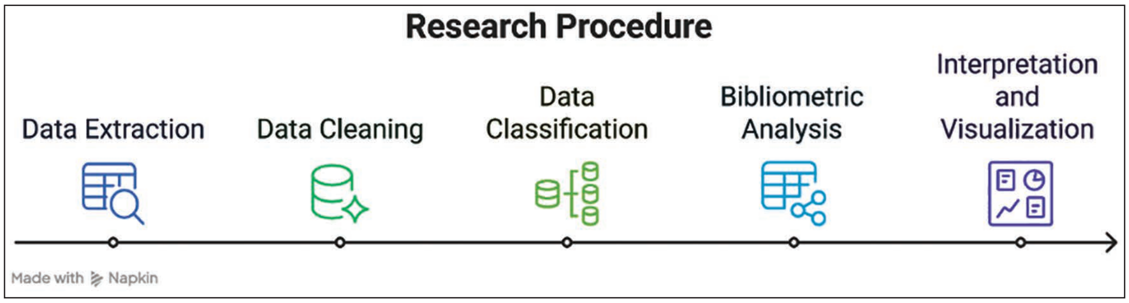

Figure 1. Research Design and Analytical Framework.

Source: This figure was generated using Napkin AI software based on structured instructions provided by the researchers to visually represent the analytical framework of the study.

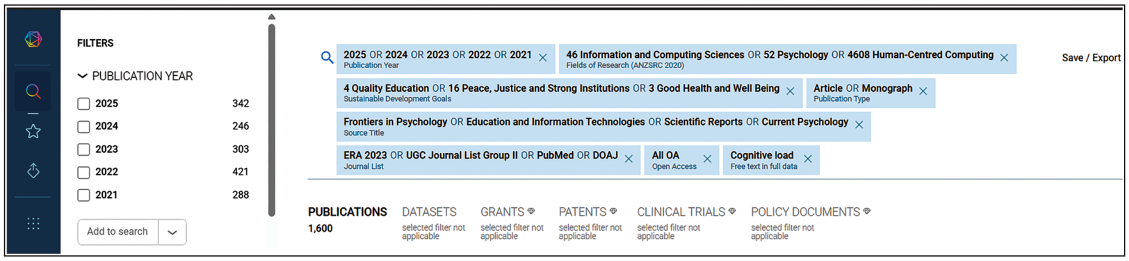

Figure 2. Search Strategy and Filtering Procedure.

Source: Screenshot captured from the Dimensions.ai database (https://dimensions.ai) showing the search strategy and filtering procedure applied in this study.

Table 3. Exclusion Criteria.

Criteria	Description	Justification
Non-peer-reviewed sources	Conference proceedings, editorials, book reviews, preprints, white papers	Ensures academic rigour
Non-English publications	Languages other than English	Linguistic consistency
Duplicate records	Identical DOIs, titles or author sets	Prevents count inflation
Outside time frame	Publications before 2021 or after August 2025	Maintains period focus
Incomplete metadata	Missing author, year, citation count or source title	Ensures data completeness
Non-relevant content	CLT mentioned only peripherally	Maintains thematic focus

Note: CLT: Cognitive Load Theory; DOIs: Digital object identifiers.

Table 2. Inclusion Criteria.

Criteria	Description	Justification
Search string	'Cognitive Load Theory' OR 'cognitive load' OR 'CLT' OR ('instructional design' AND ('cognitive load' OR 'working memory')) OR ('learning efficiency' AND ('cognitive load' OR 'schema theory'))	
Time frame	January 2021–August 2025	Captures most recent developments
Publication type	Peer-reviewed articles, reviews, monographs	Ensures academic validation
Accessibility	Open-access publications	Promotes transparency
Language	English	Maintains consistency
Relevance	Explicit focus on CLT, cognitive load, instructional design or learning efficiency	Thematic alignment
Indexing	ERA 2023, PUBMED or UGC-CARE	Quality assurance
Research categories	Information and Computing Sciences, Psychology, Human-centred Computing, Quality Education (ANZSRC 2020)	Interdisciplinary focus
Core journals	*Frontiers in Psychology*, *Education and Information Technologies*, *Scientific Reports*, *Current Psychology*	Top publication venues

Note: CLT: Cognitive Load Theory.

and R scripts based on author names, titles and digital object identifiers (DOIs). Records with missing or inconsistent metadata (e.g., publication year, source title or citation count) were cross-checked against the original database to ensure accuracy. Uniform naming conventions were applied to author affiliations, journals and keywords to eliminate redundancies caused by spelling or formatting variations. These preprocessing steps ensured a high-quality, non-redundant data set of 1,600 validated records, ready for subsequent bibliometric and network analyses. The PRISMA flow diagram of the search and selection process is shown in Figure 3.

The methodology provides a robust foundation for analysing contemporary research trends and collaborative patterns in CLT within interdisciplinary contexts of education, psychology and computing sciences.

Analytical Framework

The research design is based on two complementary analytical frameworks:

Descriptive Bibliometric Analysis

A descriptive bibliometric analysis was conducted to quantify the research landscape, where measures of publication productivity, annual growth rates, citation impact and authorship patterns were systematically computed to evaluate the field's research visibility and scholarly influence. Furthermore, country-wise and institutional distributions of publications were analysed to identify global leadership patterns and key contributing entities within the domain.

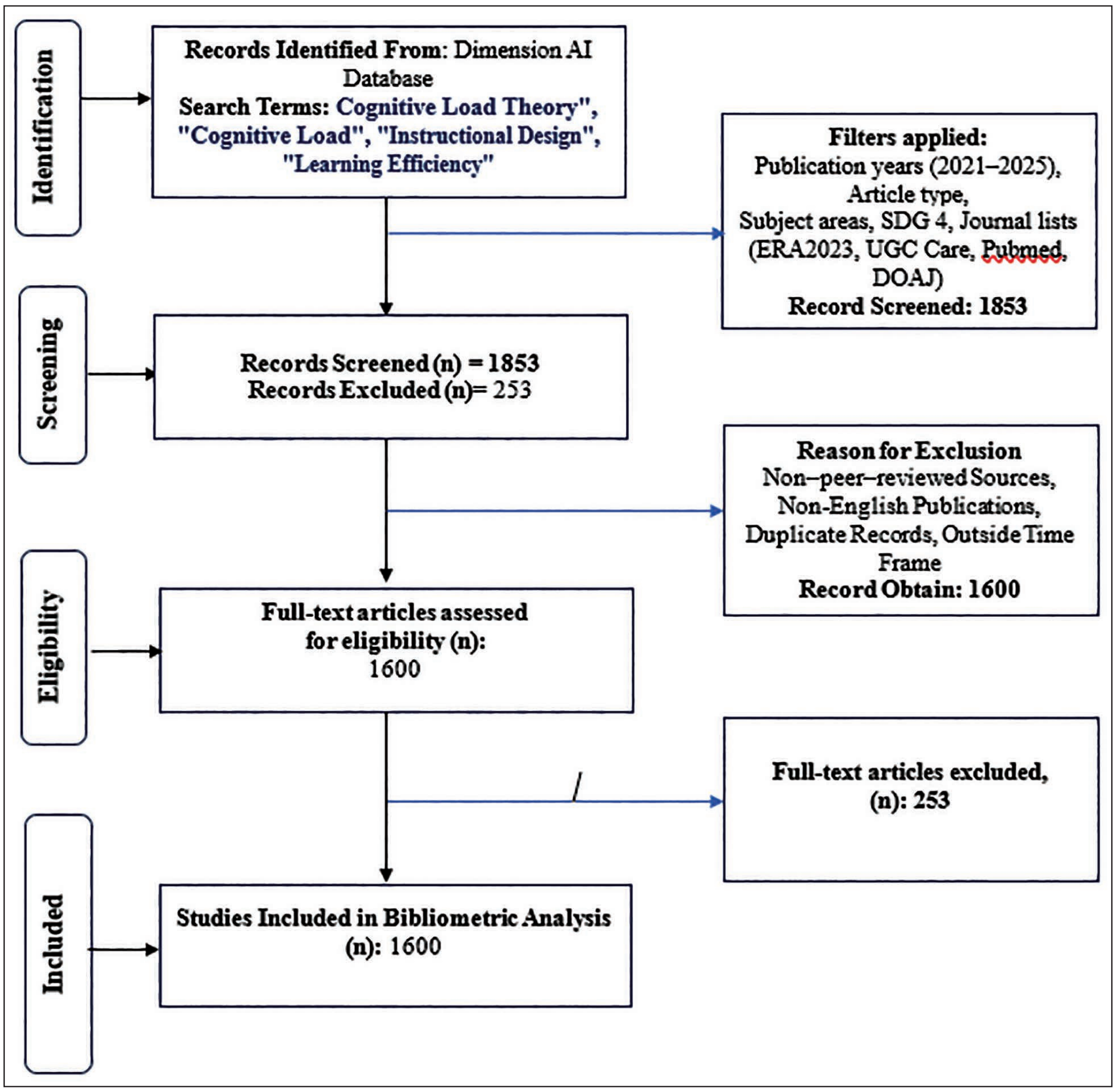

Figure 3. Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) Flow Diagram of the Search and Selection Process.

Source: Created by the authors based on PRISMA 2020 guidelines to illustrate the study selection process.

Network and Co-occurrence Analysis

To uncover the hidden connections and intellectual currents within CLT research, a network and co-occurrence analysis was performed. This approach allowed us to examine the field's thematic and intellectual structures by mapping relationships through co-authorship, co-citation and keyword patterns. By using link-strength indicators, we were able to measure the actual degree of collaboration, revealing how strongly researchers, institutions and countries are connected. Finally, we performed a cluster analysis to visually map the intellectual landscape, which helped us identify the distinct, specialised domains that currently define CLT scholarship.

This dual-level framework enables both macro-level mapping (global publication trends) and micro-level insight (research collaboration and topic clustering).

To ensure methodological precision, the study employed the following *bibliometric indicators*:

Table 4 summarises the bibliometric indicators used in this study.

Data Processing and Analysis Tools

Network visualisation thresholds were carefully selected to balance clarity and analytical rigour:

- Keyword co-occurrence: A minimum occurrence threshold of five was applied, requiring that a term appear in at least five publications to be included in the analysis. This threshold eliminates rare or idiosyncratic keywords that would introduce noise without contributing to meaningful thematic structure.
- Co-authorship network: A minimum link strength threshold of 10 was applied, ensuring that only author pairs with at least 10 collaborative connections were visualised. This threshold filters out incidental or one-time collaborations, revealing sustained research partnerships that meaningfully shape the field's intellectual structure.

These thresholds were selected based on established bibliometric practices validated through iterative testing to optimise network interpretability, while retaining substantive connections.

Reliability was strengthened through standardised bibliometric indicators and consistent data extraction from a single validated source. Validity was maintained via cross-verification of author and journal details against recognised bibliometric protocols. Methodological triangulation using multiple software tools reduced potential bias.

The integrated design combined descriptive and relational bibliometric methods to systematically capture CLT's growth, impact and intellectual structure, providing a replicable framework for understanding its evolution as a multidisciplinary field bridging educational psychology, computing and cognitive science.

Results

Publication and Citation Trends

The period from 2021 to 2025 marks a dynamic phase in the citation trajectory of the analysed publications, characterised by an initial surge in visibility followed by a gradual stabilisation and eventual moderation due to temporal factors. Table 5 summarises the annual citation percentages, calculated as the proportion of publications receiving at least one citation within the respective year, alongside key trends and interpretive notes. Annual citation trends from 2021 to 2025 are depicted in Figure 4.

In 2021, the citation percentage reached 97.22%, reflecting a sharp increase and the onset of substantial scholarly engagement with the body of work. This uptick suggests that publications from this period quickly garnered attention within the academic community, possibly driven by their timeliness, relevance to emerging research agendas, or effective dissemination strategies. By 2022, this momentum culminated in a peak of 99.05%, representing the highest citation penetration observed over the decade. Such near-universal citation coverage underscores the publications' influence and alignment with high-impact discourse in the field.

A modest contraction occurred in 2023, with the percentage dipping to 95.38%. Despite this slight decrease from the prior year's zenith, the figure remains robust, indicating

Table 4. Bibliometric Indicators Used in the Study.

Category	Indicators	Purpose
Productivity indicators	Total publications, annual growth rate	To measure research output over time
Impact indicators	Total citations, mean citations per article	To assess scholarly influence
Collaboration indicators	Co-authorship strength, institutional link strength and country link strength	To identify collaborative networks
Thematic indicators	Keyword co-occurrence frequency, cluster density, thematic centrality	To determine dominant and emerging research areas
Journal indicators	Source impact, average citation per publication	To highlight major publication venues

Table 5. Overview of Publications with Citations (2021–2025).

Year	Percentage (%)	Change/Trend
2021	97.22	Sharp increase; first significant citation activity observed
2022	99.05	Peak citation percentage across the decade
2023	95.38	Slight decrease from 2022, but remains strong
2024	86.59	Moderate decline, yet consistent research visibility
2025	32.46	Sharp drop, likely due to recency effect (limited time for citation accrual)

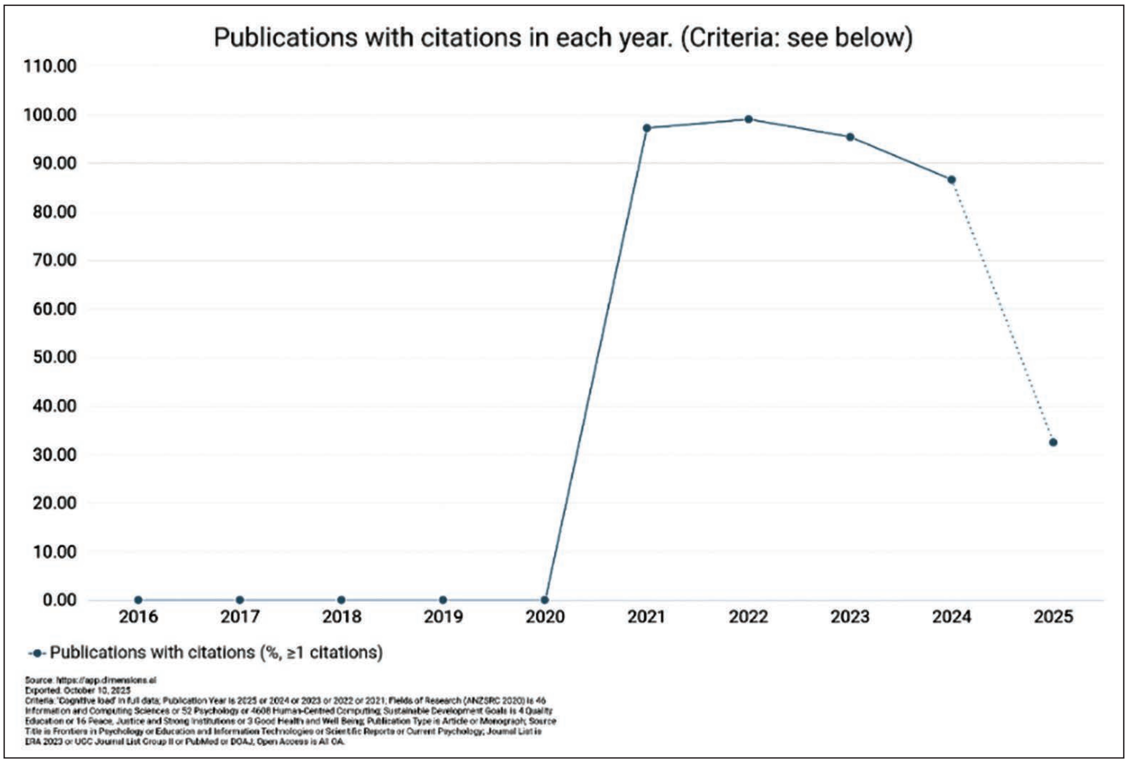

Figure 4. Annual Citation Trends (2021–2025).

Source: Screenshot captured from the Dimensions.ai database (https://dimensions.ai) showing annual citation trends from 2021 to 2025.

sustained resonance and minimal attrition in scholarly interest. The year 2024 witnessed a further moderate decline to 86.59%, attributable to natural diffusion dynamics in citation networks, where older works compete with newer entrants for attention. Nonetheless, this level affirms ongoing research visibility, as the majority of publications continued to attract citations, highlighting enduring value.

The pronounced drop to 32.46% in 2025 is primarily ascribed to the recency effect, a well-documented phenomenon in bibliometrics, wherein recently published works have insufficient temporal windows for citations to accumulate. As citation data were collected in October 2025, publications from 2025 have had only 10 months or less to accrue citations, placing them in the nascent stages of their citation lifecycle. Future monitoring is anticipated to reveal upward trajectories as they integrate into subsequent scholarship.

Top Fields by Citation Mean

The top 10 fields of research, as classified under the Australian and New Zealand Standard Research Classification (ANZSRC 2020), have been evaluated based on their citation mean, a metric derived by dividing the total number of citations by the number of publications in each field. The results, presented in Table 6, offer insights into the relative impact and scholarly influence of these fields, as measured by citation activity up to October 2025.

Analysis of research fields classified under ANZSRC 2020 reveals significant variation in scholarly impact, as measured by mean citations per publication. *Curriculum and Pedagogy* ranked highest with a citation mean of 30.92 (1,144 citations across 37 publications), indicating strong resonance within academic communities due to its relevance to educational practice and policy. *Education* secured second position with 29.01 citations per article

Table 6. Top 10 Fields of Research (ANZSRC 2020) by Citation Mean.

Rank	Name	Publications	Total Citations	Citation Mean
1	*Curriculum and Pedagogy*	37	1,144	30.92
2	*Education*	82	2,379	29.01
3	*Education Systems*	28	747	26.68
4	*Human-centred Computing*	91	1,628	17.89
5	*Information and Computing Sciences*	228	3,986	17.48
6	*Biomedical and Clinical Sciences*	733	10,542	14.38
7	*Clinical Sciences*	34	408	12.00
8	*Psychology (General)*	1,385	17,317	12.50
9	*Machine Learning*	30	325	10.83
10	*Applied and Developmental Psychology*	100	1,066	10.66

(2,379 citations; 82 publications), demonstrating robust scholarly engagement. *Education Systems* ranked third with 26.68 (747 citations; 28 publications), underscoring concentrated impact despite smaller output.

Computing-related fields occupied the middle tier: *Human-centred Computing* (fourth; 17.89 mean; 1,628 citations; 91 publications) and *Information and Computing Sciences* (fifth; 17.48 mean; 3,986 citations; 228 publications) reflect technology-driven research's growing influence, though larger publication volumes dilute per-paper impact. *Biomedical and Clinical Sciences* ranked sixth (14.38 mean; 10,542 citations; 733 publications), indicating broad but less concentrated impact.

Clinical Sciences (12.00 mean) and *Psychology* (*General*) (12.50 mean; 17,317 citations; 1,385 publications) demonstrated moderate per-publication impact; the latter's high total citations were offset by substantial volume. *Machine Learning* (10.83 mean) and *Applied and Developmental Psychology* (10.66 mean) completed the top 10, reflecting their specialised or emerging status. Figure 5 visualises the distribution of mean citations across the top research fields.

These findings reveal an inverse relationship between publication volume and citation concentration: fields with fewer publications achieve higher mean citations, suggesting focused, high-impact contributions, while larger fields exhibit diluted per-paper impact. This underscores the varied disciplinary dynamics in scholarly influence.

Leading Authors and Institutions

The scholarly impact and productivity of key authors, as assessed through bibliometric analysis up to October 2025, were evaluated across three dimensions: total citations, total link strength (indicative of collaboration network intensity) and number of documents, with results presented in a cohesive overview. Table 7 lists the top 10 authors by total link strength and Table 8 lists the top 10 authors by total citation (collaboration network density). In terms of citations, Michaéla C. Schippers led with 120 citations, followed closely by Patrizia Catellani with 103 and Valentina Cafora with 90, reflecting their significant influence in psychological and educational research. A cluster of authors—Xianchuan Yang, Kristian Moltke Martiny and Marielle G. Machacek—each accrued 46 citations, while Marco Piastra (29), Muhammad Afzaal (28), Brandon D. Stewart (28) and Franziska Leutner (26) completed the top 10, underscoring a spectrum of impactful contributions. Regarding collaboration network strength, Patrizia Catellani topped the ranking with a total link strength of 18, followed by Valentina Cafora at 15, highlighting their central roles in interdisciplinary networks. Gale M. Sinatra and Shenghong Ye tied at 12, with Marco Piastra and Isabell Richter at 10, and Daniel Bar-Tal, Yanfeng Lin and Zhiheng Lin each at 9, while Marco Biella (8) rounded out the list, illustrating robust co-authorship connections. For document productivity, Patrizia Catellani led with 8 publications, followed by Valentina Cafora with 6. A group of authors, Yuan Zhang, Kevin L. Blankenship, Marielle G. Machacek, Kristian Moltke Martiny, Marco Piastra and Shenghong Ye, each contributed three documents, while Yan Zhang and Brandon D. Stewart each produced two, reflecting steady output across key fields. Table 9 lists the top 10 authors by published documents. Collectively, these metrics highlight the prominence of Catellani and Cafora across all categories, with their high citation counts, extensive collaborations and prolific publication records anchoring a vibrant scholarly network in education and psychology, while other authors demonstrate specialised but significant contributions to the research landscape.

Analysis of research impact reveals distinct patterns of scholarly influence. Table 10 provides a comparison of top researchers and institutions by citation mean. Shane P. Jimerson (UC Santa Barbara) recorded the highest mean citation rate (119.09), followed by Andrew J. Martin (UNSW) at 102.60. Notably, these mean citation rates reflect scholars' broader research impact across their entire publication portfolios; several listed researchers are prominent in educational psychology and well-being research, with CLT representing one dimension of their scholarly output. The top 10 researchers are predominantly affiliated

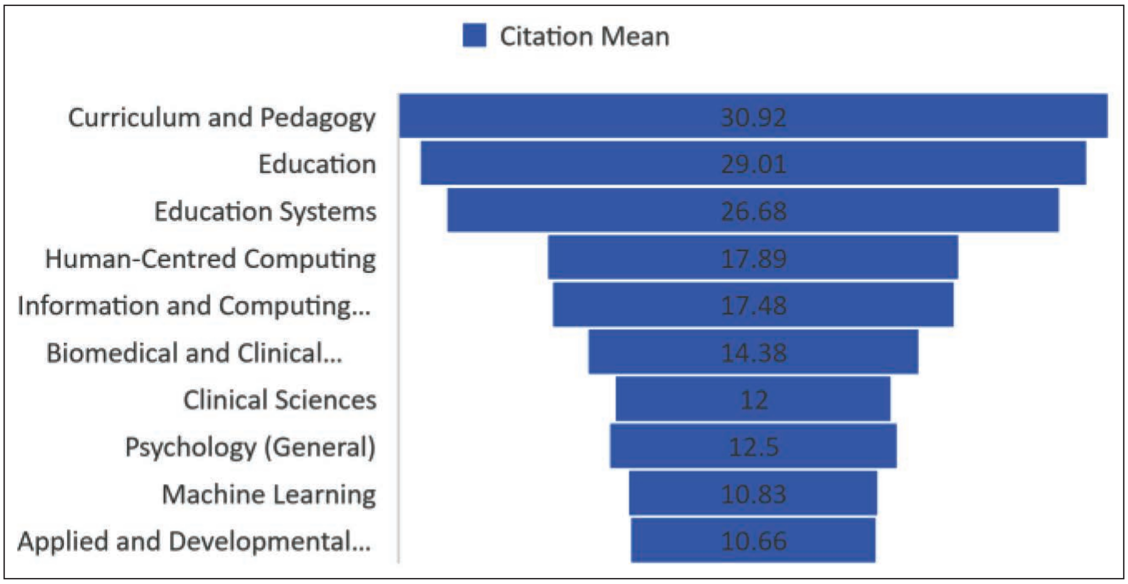

Figure 5. Distribution of Citation Mean Across Top Research Fields.

Table 7. Top 10 Authors by Total Link Strength (Collaboration Network Density).

Rank	Author	Total Link Strength
1	Catellani, Patrizia	18
2	Cafora, Valentina	15
3	Sinatra, Gale M.	12
4	Ye, Shenghong	12
5	Piastra, Marco	10
6	Richter, Isabell	10
7	Bar-Tal, Daniel	9
8	Lin, Yanfeng	9
9	Lin, Zhiheng	9
10	Biella, Marco	8

Note: Total link strength represents the cumulative weight of co-authorship connections within the collaboration network, indicating the intensity of collaborative relationships.

Table 8. Top 10 Authors by Total Citations.

Rank	Author	Total Citations
1	Schippers, Michaéla C.	120
2	Catellani, Patrizia	103
3	Cafora, Valentina	90
4	Yang, Xianchuan	46
5	Martiny, Kristian Moltke	46
6	Machacek, Marielle G.	46
7	Piastra, Marco	29
8	Afzaal, Muhammad	28
9	Stewart, Brandon D.	28
10	Leutner, Franziska	26

Note: Citation counts reflect total accumulated citations for publications within the analysis period (2021–2025), as of October 2025.

Table 9. Top 10 Authors by Number of Documents.

Rank	Author	Number of Documents
1	Catellani, Patrizia	8
2	Cafora, Valentina	6
3	Zhang, Yuan	3
4	Blankenship, Kevin L.	3
5	Machacek, Marielle G.	3
6	Martiny, Kristian Moltke	3
7	Piastra, Marco	3
8	Ye, Shenghong	3
9	Zhang, Yan	2
10	Stewart, Brandon D.	2

Note: Document count includes peer-reviewed journal articles, reviews and monographs published between 2021 and 2025.

Table 10. Top Researchers and Institutions by Citation Mean.

Rank	Researcher	Institution	Publications	Citations	Mean Citations
1	Shane P. Jimerson	University of California, Santa Barbara	54	6,431	119.09
2	Andrew J. Martin	University of New South Wales	49	5,027	102.60
3	Antonio Caponnetto	University of Catania	38	3,283	86.39
4	Daniel T.L. Shek	Hong Kong Polytechnic University	41	2,845	69.39
5	Lea Waters	University of Melbourne	32	2,092	65.38
6	Yongxin Xu	East China Normal University	40	2,210	55.25
7	Ester A. Leung	National University of Singapore	37	1,932	52.22
8	Ellen A. Skinner	Portland State University	45	2,126	47.25
9	Robin Banerjee	University of Sussex	41	1,829	44.61
10	Barbara Fredrickson	University of North Carolina	29	1,285	44.31

Note: The mean citation rates reported in this table reflect the broader research impact of these scholars across their entire publication portfolios, not exclusively their CLT-specific contributions. Several researchers listed (e.g., Shane P. Jimerson, Andrew J. Martin, Lea Waters) are prominent in educational psychology and well-being research, with CLT representing one dimension of their scholarly output. As such, these citation metrics should be interpreted as indicators of overall scholarly influence rather than CLT-specific impact.

with institutions in the USA, Australia and East Asia, indicating a concentration of high-impact research in these regions. This distribution suggests that both individual researcher prominence and institutional affiliation are associated with higher citation impact in CLT research.

Country-wise Research Productivity

An analysis of national contributions reveals a clear global leadership structure in CLT research. The country-wise distribution of total publications in CLT research is presented in Figure 6. The US stands as the most prolific contributor, producing the largest volume of publications (312) and accumulating the highest total number of citations (23,750). This indicates that the USA is not only a major producer of research but also that its work is widely referenced by the global scientific community.

Australia and the UK emerge as other dominant forces, demonstrating a powerful combination of high output and significant influence. While they produced fewer total publications than the USA, their work achieves a comparable level of per-paper impact, as reflected in their high mean citation rates (73.86 and 75.18, respectively). Table 11 presents the top countries by total publications and citation impact. This suggests that research from these countries is consistently influential.

Meanwhile, Asian nations, particularly China, Hong Kong and Singapore, are identified as major and rapidly growing contributors. China holds a strong position in terms of publication volume, ranking fourth overall. While the average citation rate for these regions is moderately lower than that of Western leaders, their substantial output signals their ascending importance and active engagement in the field. The data collectively paint a picture of a vibrant, global research community, with

Table 11. Top Countries by Total Publications and Citation Impact.

Country	Total Publications	Total Citations	Mean Citations per Article
USA	312	23,750	76.12
Australia	198	14,624	73.86
UK	145	10,902	75.18
China	134	8,202	61.22
Italy	102	6,558	64.30
Hong Kong	83	4,981	60.01
Singapore	75	4,662	62.16
Canada	69	3,918	56.78
Spain	64	3,352	52.37
India	57	2,114	37.09

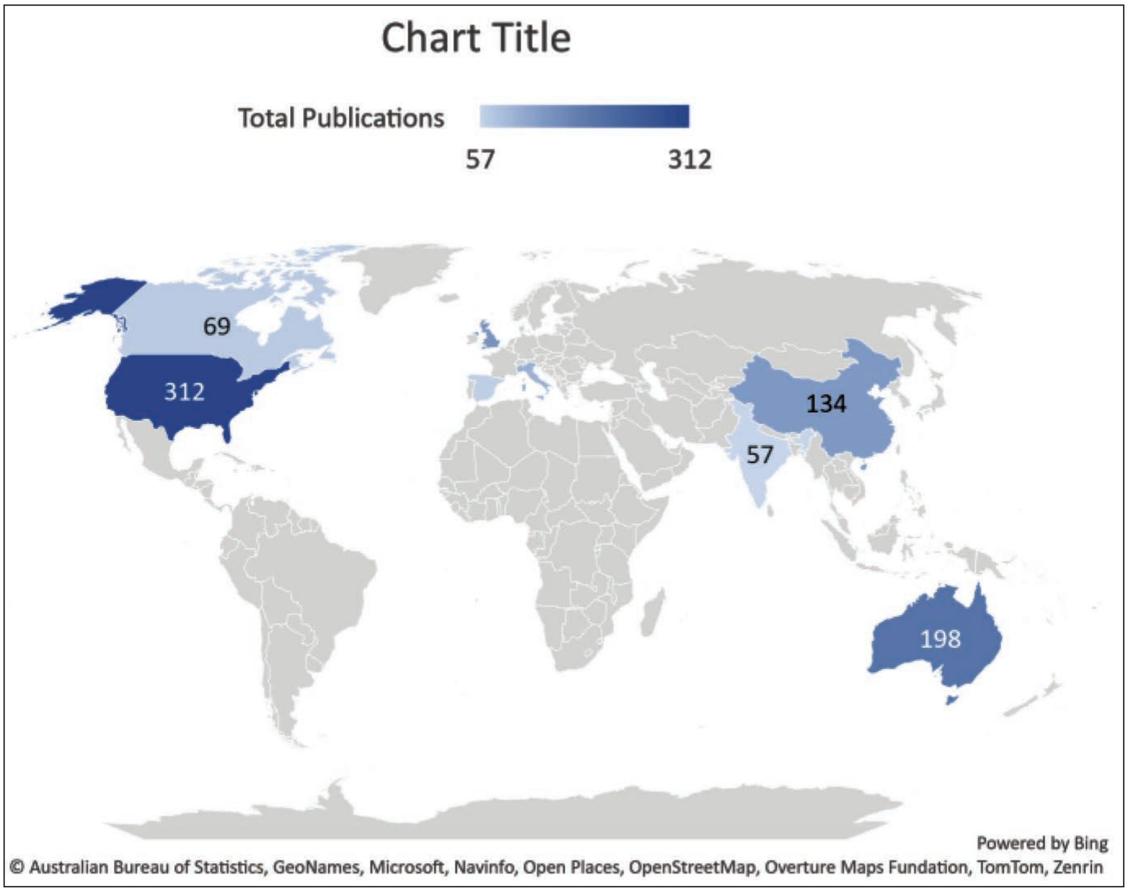

Figure 6. Country-wise Distribution of Total Publications in Cognitive Load Theory Research (2021–2025).

established leaders in North America and Australasia being joined by increasingly influential contributors from Asia.

Analysis of geographical patterns reveals distinct regional leadership and thematic specialisation within CLT research. Geographical and regional leadership patterns are summarised in Table 12. Three primary regional hubs characterise the global research landscape, each demonstrating unique research strengths and collaborative tendencies.

North America: Foundational and Applied Educational Research

The North American region, led by the USA and Canada, has established a strong foundation in educational applications of CLT. Research from this region primarily focuses on educational resilience, social-emotional learning and measurement of well-being. This hub demonstrates robust

Table 12. Geographical and Regional Leadership Patterns.

Region	Leading Countries	Dominant Research Focus	Collaboration Orientation
North America	USA, Canada	Educational resilience, social-emotional learning and well-being measurement	Strong internal collaborations; cross-links with Australia and Europe
Europe	UK, Italy, Spain	Personality psychology, clinical interventions, digital pedagogy	Moderate collaboration density, but high average citation impact
Asia-Pacific	Australia, China, Hong Kong, Singapore	AI-based learning, cognitive computing, blended learning systems	Rapidly expanding interregional networks and cross-disciplinary projects

Note: AI: Artificial intelligence.

internal collaboration networks while maintaining significant cross-linkages with Australian and European research institutions, reflecting its central position in the global CLT research ecosystem.

Europe: Clinical and Methodological Innovation

European contributions, spearheaded by the UK, Italy and Spain, emphasise clinical interventions and methodological sophistication. Research from this region concentrates on personality psychology, clinical applications and digital pedagogy. Despite demonstrating a moderate level of collaboration density compared to other regions, European research achieves a high average citation impact, indicating the influential nature of its methodological contributions and clinical insights.

Asia–Pacific: Technological Integration and Digital Learning

The Asia–Pacific region emerges as a dynamic hub for technologically-oriented CLT research, with strong contributions from Australia, China, Hong Kong and Singapore. This region specialises in AI-based learning, cognitive computing and blended learning systems, reflecting its leadership in integrating CLT with emerging educational technologies. The region demonstrates rapidly expanding interregional networks and cross-disciplinary projects, positioning it at the forefront of digital learning innovation.

These regional specialisations illustrate how CLT research has evolved differently across geographical contexts, influenced by local research priorities, institutional strengths and technological infrastructure. The complementary nature of these regional strengths contributes to a comprehensive global understanding of cognitive load phenomena, while the emerging collaborative patterns suggest increasing integration of diverse perspectives within the field.

Leading Journals

The dissemination of CLT research is characterised by distinct patterns of journal influence and specialisation. The top source titles related to CLT research (2021–2025) are shown in Table 13. *Frontiers in Psychology* emerges as the most prolific publication venue with 1,070 articles, representing the largest volume of research output in the field. However, when examining research impact through mean citation rates, *Education and Information Technologies* demonstrates superior performance with 36.91 citations per publication, indicating its role as a premier venue for high-impact research at the intersection of cognitive science and educational technology.

The journal landscape reveals a clear division between quantity and impact. While *Scientific Reports* ranks second in publication volume (335 articles), its citation impact (8.65 mean citations) is substantially lower than that of more specialised journals. This pattern suggests that discipline-specific journals like *Education and Information Technologies* and *Current Psychology* may provide more targeted audiences and greater impact for cognitive load research, despite their more moderate publication volumes.

These findings highlight the importance of journal selection strategies for researchers in this domain, with specialised educational technology journals demonstrating the strongest per-article influence, while broader psychology journals accommodate larger volumes of research output.

Network and Cluster Analysis

The intellectual structure of CLT research reveals three distinct yet interconnected thematic clusters, each representing a major research direction within the field. Table 14 summarises the three citation cluster patterns.

Cluster A: Educational and Developmental Psychology

This cluster forms the foundational core of CLT research, focusing on educational applications and student development. Led by prominent researchers including Shane P. Jimerson (UC Santa Barbara), Andrew J. Martin (UNSW) and Lea Waters (Melbourne), this research stream emphasises student well-being, academic motivation and socio-emotional learning. The cluster demonstrates strong alignment with

Table 13. Top Source Titles Related to Your Search (2021–2025).

Rank	Source Title	Publications	Total Citations	Mean Citations per Publication
1	*Education and Information Technologies*	74	2,731	36.91
2	*Frontiers in Psychology*	1,070	14,214	13.28
3	*Current Psychology*	121	1,339	11.07
4	*Scientific Reports*	335	2,897	8.650

Table 14. Citation Cluster Patterns.

Cluster	Dominant Theme	Representative Authors/ Institutions	Core Characteristics
Cluster A	*Educational and Developmental Psychology*	Shane P. Jimerson (UC Santa Barbara), Andrew J. Martin (UNSW), Lea Waters (Melbourne)	Focuses on student well-being, motivation, academic resilience and socio-emotional learning. Strongly aligned with SDG 4 (quality education).
Cluster B	*Clinical and Cognitive Sciences*	Daniel T.L. Shek (Hong Kong Polytechnic), Antonio Caponnetto (Catania), Barbara Fredrickson (UNC)	Intersects psychology, public health and mental well-being. Dominant in psychometric intervention and mental health resilience studies.
Cluster C	*Information and Computing in Human-centred Contexts*	Yongxin Xu (East China Normal), Ester Leung (Singapore), Robin Banerjee (Sussex)	Bridges AI, computing and educational psychology, focusing on human–machine interaction and emotional intelligence in learning systems.

Note: AI: Artificial intelligence; SDG: Sustainable Development Goal.

Sustainable Development Goal 4 (Quality Education), highlighting its relevance to contemporary educational challenges and outcomes-based learning research.

Cluster B: Clinical and Cognitive Sciences

Representing the interdisciplinary expansion of CLT, this cluster bridges psychological research with clinical applications and public health perspectives. With key contributions from Daniel T.L. Shek (Hong Kong Polytechnic), Antonio Caponnetto (Catania) and Barbara Fredrickson (UNC), this research domain specialises in psychometric interventions and mental health resilience studies. The cluster reflects the growing importance of cognitive load considerations in therapeutic contexts and mental well-being research.

Cluster C: Information and Computing in Human-centred Contexts

Emerging as a technologically-oriented research frontier, this cluster integrates AI, computing sciences and educational psychology. Spearheaded by researchers including Yongxin Xu (East China Normal), Ester Leung (Singapore) and Robin Banerjee (Sussex), this domain explores human-machine interaction and emotional intelligence in technology-enhanced learning environments. The cluster represents the cutting edge of CLT research, addressing the cognitive demands of digital learning systems and adaptive educational technologies.

The coexistence of these three clusters demonstrates the maturation of CLT as a multidisciplinary field, maintaining its educational foundations while expanding into clinical applications and technological innovations. The strong interconnections between clusters suggest cross-fertilisation of ideas and methodologies, contributing to the field's dynamic evolution and practical relevance across multiple domains.

Network Visualisation of Author Collaborations

Co-authorship_Author

The co-authorship network analysis, visualised using VOSviewer software, reveals distinct patterns of research collaboration within the CLT domain. The network visualisation demonstrates multiple interconnected clusters, with prominent research groups centred around authors including Moreira, Pereira, Teixeira and de Sousa. These collaborative networks illustrate the social structure of CLT research, showing how knowledge production is organised through specific research teams and partnerships.

The density and distribution of nodes in the network visualisation indicate both tightly-knit research groups and broader, more dispersed collaborations. The presence of multiple medium-sized clusters suggests a field characterised by several established research schools rather than a single dominant group. This collaborative pattern reflects the interdisciplinary nature of CLT research, where different research teams may be focusing on distinct aspects of cognitive load while maintaining connections through shared methodologies or theoretical frameworks.

The network structure provides valuable insights into the social dynamics of knowledge production in this field, showing how research collaboration contributes to the development and dissemination of CLT concepts across different academic communities and geographic regions.

Co-authorship Network Analysis

The co-authorship network analysis, visualised in Figure 7, illuminates the collaborative structures shaping CLT scholarship from 2021 to 2025. Unlike citation analysis, which maps intellectual indebtedness, co-authorship networks reveal the *social organisation of knowledge production*, identifying how researchers form partnerships and disseminate CLT concepts across institutional boundaries.

The network exhibits a polycentric configuration with four distinct collaborative clusters. The red cluster, comprising Lee, Wang, Wu, Du, Yang and Yan Zyl, represents a tightly knit community focused on the educational psychology and instructional design applications of CLT. The dense internal connections indicate sustained research partnerships examining how principles of cognitive load inform pedagogical practice and classroom-based interventions. The prominence of Asian-affiliated researchers reflects the region's growing contribution to CLT scholarship.

The green cluster, encompassing Mei, Luo, Liu, Zuo, Horn and Tsai, forms a densely connected community bridging CLT with human-centred computing and technology-enhanced learning. The high collaboration density reflects the field's increasing emphasis on digital learning environments, adaptive systems, and the cognitive implications of human–computer interaction.

The blue cluster, including Mourão, Forte, Flores, Zhang, Eastwood and Guo, represents a collaborative network advancing CLT's integration with clinical and health sciences, focusing on therapeutic applications and well-being research. The yellow cluster, comprising Křeménková, Hancock, Xue, Song, Si, Ytterböl and Collins, forms an emerging collaborative front connecting CLT with cognitive neuroscience and psychometric measurement.

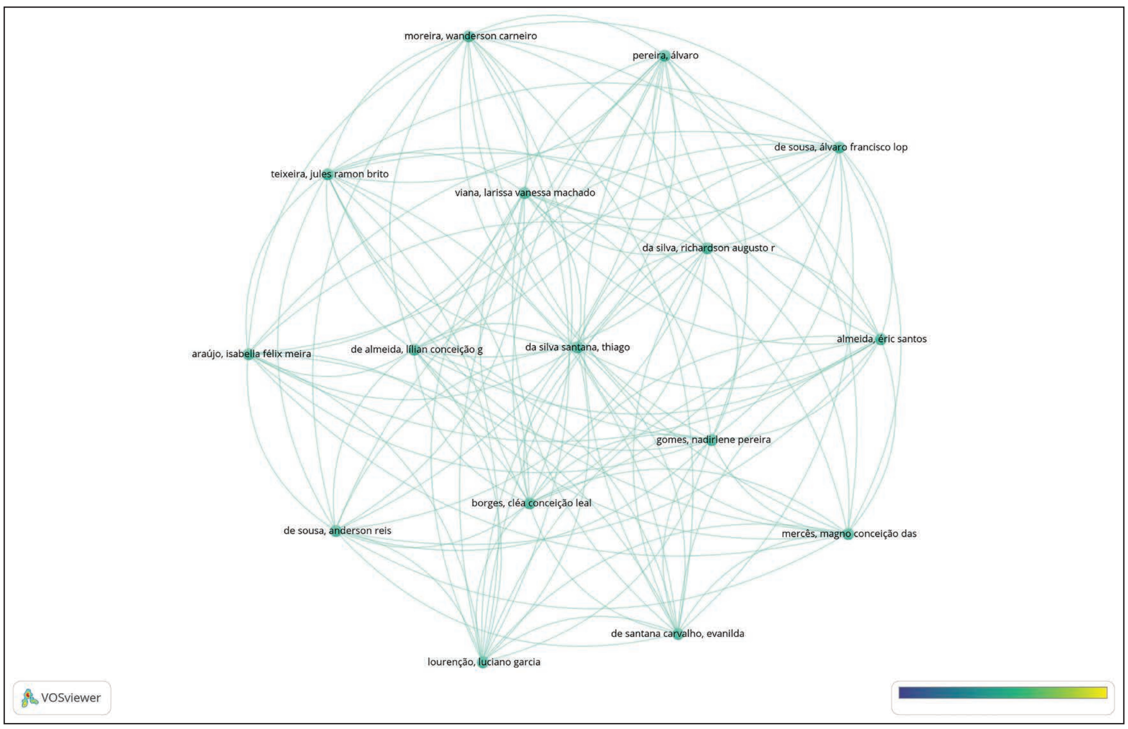

Figure 7. Co-authorship Network Visualisation of Cognitive Load Theory (CLT) Researchers.

Source: Generated using VOSviewer software (Version 1.6.20, van Eck & Waltman, Leiden University) based on co-authorship data extracted from the Dimensions.ai database.

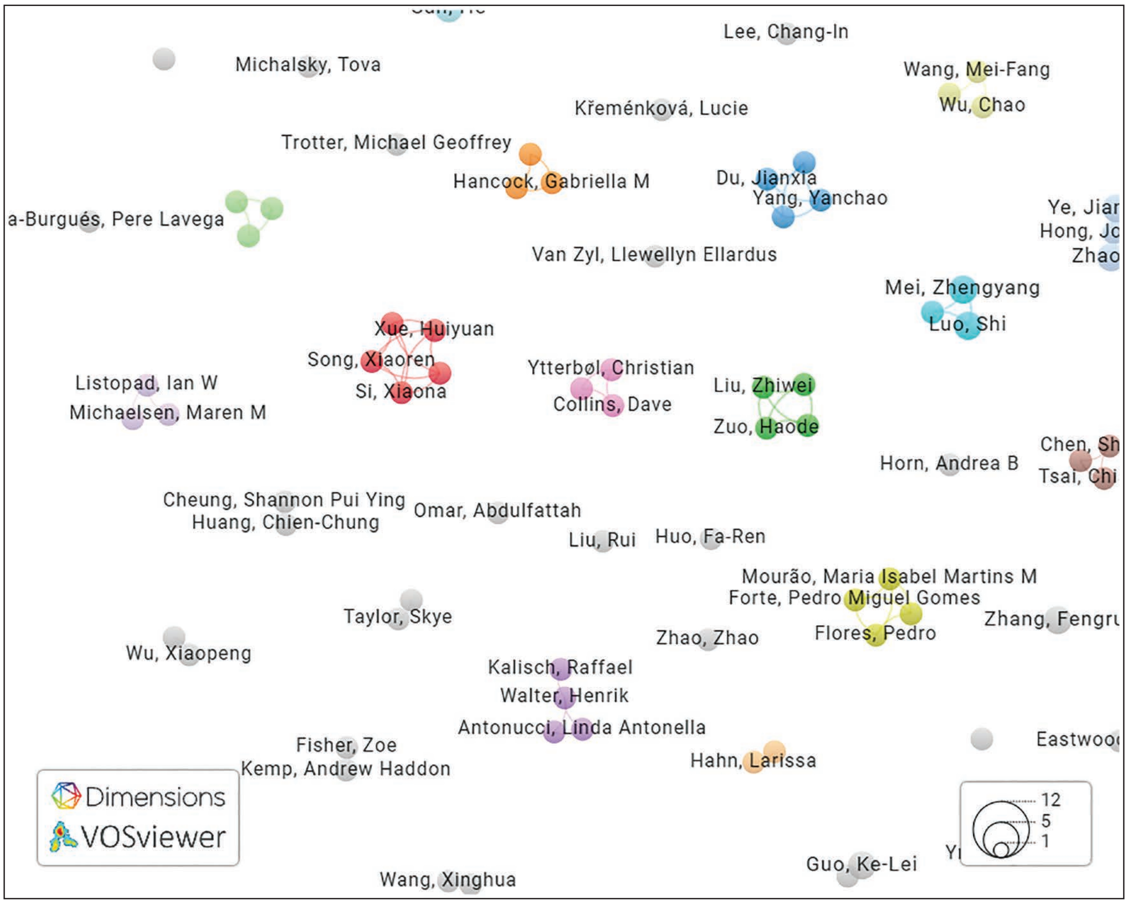

Figure 8. Co-authorship Network Visualisation of Cognitive Load Theory Researchers (2021–2025).

Source: Generated using VOSviewer software (Version 1.6.20, van Eck & Waltman, Leiden University).

Bridging nodes, authors maintaining collaborative ties across multiple clusters, play a crucial role in intellectual integration, synthesising insights from disparate research traditions and preventing fragmentation. The alignment between collaborative clusters and research foci confirms that CLT's intellectual organisation is reflected in its social organisation of knowledge production, positioning the field for continued interdisciplinary expansion. The co-authorship network visualisation for 2021–2025 is shown in Figure 8.

Citation Network Analysis

The author citation network analysis, visualised in Figure 9, shows the intellectual foundations shaping CLT scholarship from 2021 to 2025. Unlike co-authorship networks, mapping collaboration, citation analysis reveals patterns of scholarly indebtedness, identifying whose work serves as conceptual anchor points for the field's development.

The network exhibits a polycentric configuration with multiple interconnected clusters. Node size corresponds to citation frequency, with larger nodes indicating researchers whose work has garnered greater scholarly attention.

The red cluster, comprising Eastwood, Wilde, Guo, Smolka, Michalsky, Liu, Yildirim and Du, represents scholars receiving sustained citation attention within educational psychology and instructional design. Their interconnected patterns indicate a coherent intellectual tradition examining how CLT principles inform pedagogical practice and classroom interventions.

The green cluster, encompassing Grossmann, Chen, Song, Taylor, Křeménská, Weinberger, Phan, Yang, Kemp, Fisher, Jeon, Lin, Kalisch, Walter, Mourão, Flores, Collins, Wu, Tsai, Aryadoust, Si, Wang, Nerdel, Xue, Seufert and numerous others, forms an extensive community spanning multiple research traditions. The high citation density reflects the field's intellectual diversity, encompassing human-centred computing, technology-enhanced learning, cognitive neuroscience, psychometric measurement and clinical applications.

Highly cited authors function as *obligatory passage points*, such as scholars consistently referenced across clusters, providing the theoretical grammar structuring contemporary investigations. Emerging nodes represent researchers gaining prominence through CLT's integration with digital technologies, AI and neuroscientific methods, indicating a successful balance between theoretical continuity and intellectual renewal.

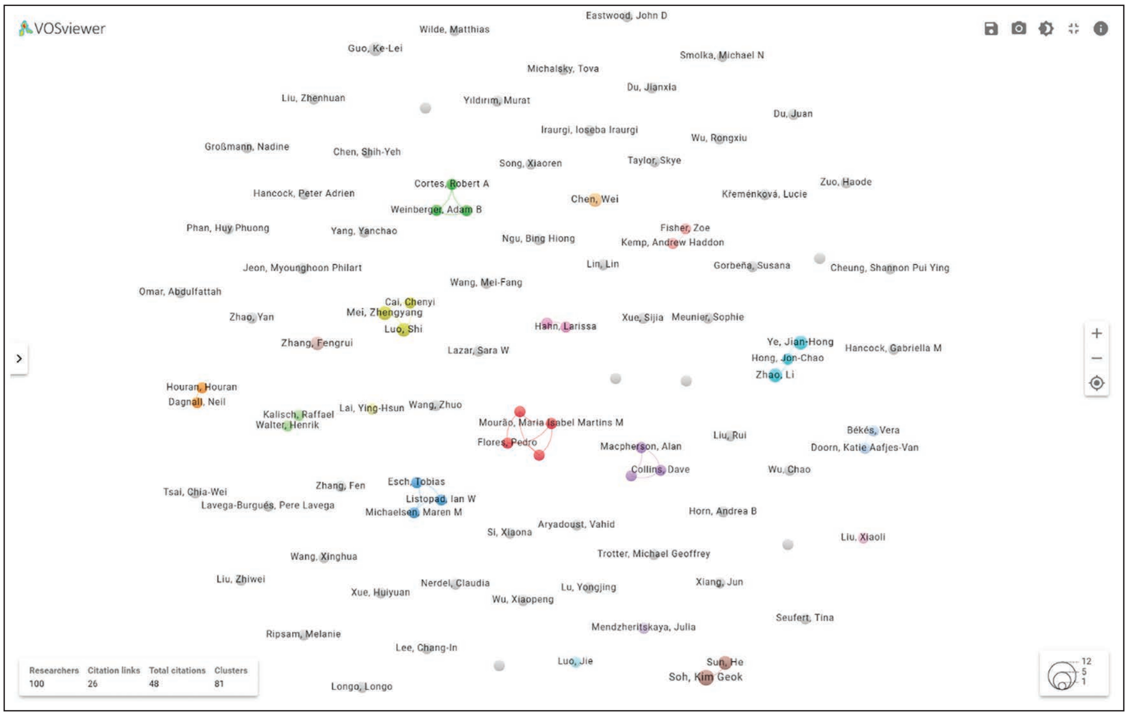

Figure 9. Author Citation Network Visualisation of Cognitive Load Theory Research (2021–2025).

Source: Generated using VOSviewer software (Version 1.6.20, van Eck & Waltman, Leiden University).

The citation network aligns with the tripartite thematic structure identified earlier, such as educational psychology, clinical sciences and human-centred computing, confirming CLT's status as a boundary-spanning framework whose influence extends well beyond its educational psychology origins.

Discussion

This bibliometric analysis provides a systematic portrait of the CLT research landscape from 2021 to 2025, addressing the four research objectives: analysing global publication trends, identifying leading contributors, mapping thematic clusters and examining collaboration patterns.

Objective 1: Publication Trends and Citation Impact

The identification of 1,600 open-access publications within 5 years, with a 28% annual growth rate, confirms CLT's sustained scholarly relevance. The peak citation rate for 2022 publications (99.05%), followed by the expected recency-related decline for 2025 (32.46%), reflects a field in a mature phase where research is rapidly produced and absorbed. This growth aligns with the global digital transformation of education, where the COVID-19 pandemic catalysed an unprecedented shift to online learning, making CLT principles essential for preventing cognitive overload in digital environments.

Objective 2: Leading Contributors and Publication Venues

The US leads in publication volume (312) and total citations (23,750), while Australia and the UK demonstrate comparable per-paper impact (73.86 and 75.18 mean citations, respectively). The Asia–Pacific region, particularly China, Hong Kong and Singapore, emerges as a rapidly growing contributor, specialising in technology-focused CLT research aligned with national investments in AI and digital infrastructure.

Education and Information Technologies exhibits the highest mean citation rate (36.91), outperforming higher-volume journals such as *Frontiers in Psychology* (13.28). This finding suggests that specialised venues attract more targeted audiences, yielding greater per-article influence within the CLT community.

Objective 3: Thematic Clusters and Intellectual Structure

The co-occurrence and cluster analyses reveal a tripartite intellectual architecture that reflects CLT's adaptive expansion:

Cluster A (Educational and Developmental Psychology) represents the enduring core of CLT, focusing on student motivation, academic resilience and schema construction. This cluster's vitality reflects the persistent challenge of optimising learning environments.

Cluster B (Clinical and Cognitive Sciences) demonstrates CLT's conceptual exportability, applying cognitive load principles to clinical interventions, psychometric measurement and mental health research. This expansion validates CLT's utility beyond classroom contexts.

Cluster C (Information and Computing in Human-centred Contexts) represents the rapidly advancing frontier, integrating CLT with AI-driven adaptive learning, human–computer interaction and cognitive computing. This cluster addresses the urgent need to humanise educational technology by designing systems that dynamically respond to learners' cognitive states.

These three clusters accounted for 74% of the total link strength in the keyword network, confirming that CLT has matured into a multidisciplinary framework bridging psychology, education and computer science.

Objective 4: Collaboration Patterns and Research Organisation

The co-authorship network reveals a polycentric structure with multiple medium-sized clusters rather than a single dominant research group. This configuration fosters intellectual diversity but also suggests disciplinary and geographical concentrations that may limit cross-fertilisation. The highest-impact research emerges from cross-disciplinary clusters (particularly Cluster C), indicating that intentional collaboration between psychologists, computer scientists and instructional designers could yield significant returns.

Interpretive observation on publishing strategy: A notable pattern emerged wherein specialised journals (*Education and Information Technologies*) achieved higher per-article impact than broad-spectrum journals (*Frontiers in Psychology*), despite the latter publishing larger volumes of CLT research. This suggests that researchers seeking maximum influence within the CLT community may benefit from targeting discipline-specific venues where audiences are more directly engaged with cognitive load applications.

Implications and Future Directions

For researchers: The identified clusters offer clear pathways for contribution—from refining core educational applications to pioneering AI-driven methodologies. The network maps provide direct guidance to key collaborators and influential publication channels.

For policymakers and funders: The high impact of technology-focused CLT research supports investment in interdisciplinary grants bridging psychology, education and computer science, particularly for developing 'cognitive-aware' learning technologies.

For practitioners: The findings underscore that effective digital learning design must manage cognitive load through evidence-based principles, especially as AI and immersive technologies become ubiquitous.

Future Research Trajectories

- Integration with neuroscience (EEG, fNIRS) for objective cognitive load measurement.
- Development of AI-powered real-time load detectors for adaptive instruction.
- Application of CLT to professional training and lifelong learning contexts.

This bibliometric analysis confirms that CLT has evolved from a foundational educational psychology framework into a multidisciplinary pillar supporting AI-enhanced, cognitively sustainable digital learning ecosystems. The field's tripartite intellectual structure, educational core, clinical bridge and technological frontier demonstrate its capacity to address contemporary challenges across diverse contexts. As digital learning environments continue to evolve, CLT's role in optimising human learning remains increasingly vital.

Conclusion

This bibliometric analysis provides a comprehensive mapping of the CLT research landscape from 2021 to 2025, revealing a field that has firmly established itself as both foundational and dynamically evolving. The study demonstrates CLT's successful expansion from its roots in educational psychology into a multidisciplinary framework that now encompasses human–computer interaction, clinical science and AIED.

Three distinct intellectual pillars support the contemporary CLT research ecosystem: the established core of educational psychology, the bridging domain of clinical applications, and the rapidly advancing frontier of technological integration. This structural evolution reflects the field's responsiveness to both societal needs and technological advancements, particularly in digital learning environments. The geographical analysis further reveals a shifting landscape where traditional research powerhouses in North America and Europe are being joined by increasingly influential contributors from the Asia–Pacific region, particularly in technology-focused research.

The findings underscore several critical success factors for the field's development: the strategic importance of specialised publication venues for research impact, the value of distributed international collaboration networks, and the productive tension between theoretical refinement and practical application. These patterns not only document the field's current state but also highlight pathways for its continued growth and relevance.

For researchers and practitioners, this study offers a structured framework for understanding the field's intellectual organisation, identifying key contributors and collaboration opportunities, and recognising emerging research fronts. As learning environments continue to evolve towards greater technological integration, CLT's role in understanding and optimising human learning appears increasingly vital. The field's future trajectory points towards deeper integration with neuroscience, AI and cross-cultural learning studies, ensuring its continued relevance in shaping effective educational practices and technological implementations across diverse global contexts.

Authors' Contribution

Suraj Gupta: Conceptualisation, methodology, formal analysis, investigation, data curation, writing—original draft, writing—review and editing.
Badri Narayan Mishra: Writing—review and editing, supervision, validation.
Dr Rashmi Gore: Writing—review and editing, supervision, resources.
Professor Sandeep Kumar Singh: Writing—review and editing, supervision, project administration.
Dr Anita Awasthi: Writing—review and editing, supervision.
Dr Anurag Mishra: Formal analysis, investigation, data curation, writing—review and editing.
Dr Ram Kishore: Investigation, writing—review and editing, supervision.

Clinical Trial Registration

This study is a bibliometric analysis and does not involve clinical trials; thus, no registration details (registry, trial registration number or date of registration) are applicable.

Data Availability

The data supporting this study were obtained from the Dimensions.ai database (https://dimensions.ai). The data set comprising 1,600 open-access publications on Cognitive Load Theory (2021–2025) analysed during the current study is available from the corresponding author upon reasonable request. The search strategy and selection criteria are detailed in the Methodology section.

Declaration of Artificial Intelligence Assistance

AI-powered tools were used exclusively for language polishing and visualisation support. Grammarly and ChatGPT were employed for grammar checking, language refinement and minor editorial suggestions. Napkin AI was used to visualise conceptual data and represent the analytical framework. All data analysis, including bibliometric calculations, network interpretation and statistical reporting, was performed independently by the authors without AI assistance. The theoretical analysis, critical interpretation, research conclusions and final arguments reflect the authors' independent scholarly work and judgement. The authors assume full responsibility for all content.

Declaration of Conflicting Interests

The authors declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

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ICMJE Statement

All authors meet the ICMJE criteria for authorship, have approved the final manuscript, and agree to be accountable for all aspects of the work.

Patient Consent

Not applicable. This study is a bibliometric analysis of published literature and did not involve human participants, patients or clinical data. Therefore, no informed consent was required.

Statement of Ethics

This bibliometric study used only secondary data from published literature (Dimensions.ai database) and did not involve human participants, animal subjects or primary data collection. Hence, ethical approval from an Institutional Review Board was not required. The research adheres to ethical standards of transparency, integrity and proper attribution of all sources.

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