Journal of Education and Learning Reviews, 2 (2): March-April 2025 ISSN: 3057-0387
Website: https://so19.tci-thaijo.org/index.php/JELS/about

Trends and Effects of Psychological and Cognitive Load in Education

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Received 15/11/2024	Revised 21/11/2024	Accepted 12/01/2025

Abstract

Background and Aim: The cognitive load experienced by students during learning can lead to mental fatigue and significant psychological disturbances, often resulting in negative emotional responses. This study aims to identify trends and examine influential factors in psychological aspects and cognitive load within the educational context, thereby advancing the understanding of educational psychology and cognitive load theory.

Materials and Methods: Utilizing a mixed-methods approach, the research integrates bibliometric analysis and a systematic literature review, allowing a comprehensive evaluation of scholarly trends. Research data were sourced from the Scopus database with the keywords "Psychological" AND "Cognitive Load" AND "Education" in article titles, abstracts, and keywords, ensuring alignment with relevant literature.

Results: Findings show a fluctuating trend in annual publication citations, marked by phases of notable increases and declines. These patterns are shaped by topical relevance, research quality, and shifts in the academic landscape and technology for information access. The United States leads in publication contributions, comprising 27.4% of total articles, with significant use of terms like cognitive load, learning systems, executive function, and motivation in recent research, while terms like humans, cognition, and education remain consistently emphasized. The insights suggest that innovative learning media, while enhancing outcomes, introduce complexities in managing cognitive load.

Conclusion: This study underscores the need for precise cognitive load measurement in developing effective interventions, emphasizing the management of students' emotions as a critical component in online learning and technology acceptance. These findings inform educational practices and policies by highlighting strategies that support emotional well-being and foster effective, student-centred learning environments, laying the groundwork for future research on enhancing educational practices through cognitive and emotional insights.

Keywords: Cognitive Load; Psychology; Education; Effects

Introduction

The rapid advancement of modern education is driven by technological progress and an evolving understanding of how students learn (Dede et al., 2005). A central focus in contemporary education research is the interaction between cognitive load and psychological factors, significantly shaping students' learning experiences and outcomes (Sweller, 2010). Cognitive Load Theory (CLT), proposed by Sweller, explains that cognitive load reflects the demands placed on students' memory as they process information, with different types of load (intrinsic, extraneous, and germane) influencing

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learning efficiency. Understanding and managing these cognitive loads—particularly by minimizing extraneous load—can help optimize instructional design, enabling students to more effectively encode essential knowledge into long-term memory (Chandler & Sweller, 1992; Sweller et al., 2014).

Excessive cognitive load presents new challenges, often leading to mental fatigue and negatively affecting students' emotional well-being, engagement, and attitudes toward learning environments (Skulmowski & Xu, 2022; Tzafilkou et al., 2021). Emotions play a pivotal role in learning: positive emotions like enjoyment enhance achievement, while negative emotions such as anxiety and boredom can reduce motivation and academic performance (Mega et al., 2014; Pekrun et al., 2020). With technology increasingly integrated into learning platforms, students are frequently exposed to cognitive and emotional demands distinct from traditional settings. For instance, online learning environments may lead to specific issues such as moderate to severe stress and reduced self-confidence when students encounter complex digital tasks (Husky et al., 2020; Chen et al., 2020). These dynamics underscore the importance of psychological and cognitive factors, mainly as modern education adopts digital tools, intelligent learning systems, and serious games (Graesser & D'Mello, 2012; Schrader & Nett, 2018).

Online learning theories proposed by Yan & Zhao (2019) found that negative emotions like boredom and mischievous feelings can impact students' perceived achievement, whereas positive emotions such as enjoyment result in positive achievement outcomes. Compared to traditional learning models, students are more prone to mental health issues such as moderate to severe stress (Husky et al., 2020). Depression, on the other hand, can lead to decreased self-confidence (Chen et al., 2020) when the learning process overly emphasizes technological advancement, not fully comprehended by students (Ajmal & Ahmad, 2019). Research reveals that negative emotions like boredom and cognitive load directly and indirectly impact students.

While substantial research addresses cognitive load and emotional factors, there remains a need for a cohesive understanding of how these elements interact in educational contexts. Current studies vary in focus and findings, creating gaps in understanding how these factors collectively shape learning experiences. This study aims to identify trends and examine influential factors in psychological aspects and cognitive load within the educational context, thereby advancing the understanding of educational psychology and cognitive load theory. By synthesizing trends and factors affecting cognitive load and psychological aspects, this research provides insights that may guide educators and policymakers in designing more effective, student-centred learning environments.

In addressing these objectives, this study seeks to contribute to theoretical and practical advancements in educational psychology and cognitive load management, focusing on the demands of digital learning. Integrating psychological insights with cognitive load theory supports the development of adaptive and emotionally supportive learning environments, enhancing learning outcomes and students' emotional resilience.

Literature review

Cognitive psychology examines the mental processes underpinning learning, such as attention, perception, language processing, reasoning, problem-solving, and memory (Bidzan-Bluma et al., 2024). A foundational element in cognitive psychology is memory, a cognitive function enabling students to store, process, and retrieve information. Memory can be categorized into short-term, working, and long-term memory, which work in tandem to support cognitive processing (Banikowski & Mehring, 1999). Additionally, memory can be divided into semantic memory, which handles procedural knowledge, and episodic memory, which manages new information (Wang et al., 2024). These processes are crucial in how students absorb, retain, and apply knowledge in educational settings.

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Types of Cognitive Load

Cognitive Load Theory (CLT), introduced by Sweller et al (1998), offers insights into human information processing by examining the limitations of working memory and its role in long-term memory storage. CLT identifies three types of cognitive load: intrinsic, extraneous, and germane. Each of these types uniquely affects learning:

1. Intrinsic load arises from the complexity of the material itself and the learner's expertise level (Sweller, 1994). For example, the intrinsic load is generally higher for subjects like advanced mathematics, where inherent complexity requires significant cognitive resources.
2. Extraneous Load: Extraneous load stems from how information is presented, affecting the ease with which students can process it. Effective instructional design minimizes extraneous load, allowing students to focus on essential content without being distracted by irrelevant information (DeLeeuw & Mayer, 2008; Rana & Burgin, 2017).
3. Germane Load: Germane load supports schema development and automation in long-term memory (Sweller, 2010). For example, problem-solving exercises, such as concept mapping, can enhance schema formation, promoting more profound understanding and retention (Khalil et al., 2005).

Educators can help students focus cognitive resources on processing and internalizing essential material by optimising instructional design to reduce extraneous load and promote germane load.

Psychological and Emotional Factors in Learning

Emotions, motivation, and cognitive processes are intertwined and significantly affect students' learning experiences and outcomes. Studies show that positive emotions like enjoyment can increase engagement and achievement, while negative emotions such as anxiety or boredom may impede motivation and lower academic performance (Mega et al., 2014; Pekrun et al., 2020). The control-value theory further categorizes emotions based on their valence (positive or negative) and their effects on learning. It underscores that educational emotions like frustration, boredom, and anxiety are integral to students' psychological engagement (Boekaerts & Pekrun, 2015). Emotional responses often fluctuate during tasks requiring substantial cognitive effort, especially in technologically advanced learning environments.

Negative emotions also correlate with higher cognitive load levels, potentially decreasing engagement in educational tasks (Tzafilkou et al., 2021). For instance, students may experience heightened anxiety in digital learning environments if they lack adequate skills to navigate complex technological tools, affecting their perceived achievement and satisfaction (Husky et al., 2020). Thus, understanding the emotional aspects of learning and their interaction with cognitive load is crucial for designing interventions that enhance student engagement and academic outcomes.

Cognitive Load in Technological and Digital Learning Contexts

Digital and online learning platforms introduce new cognitive and psychological demands that differ from those in traditional settings. Studies show that online learning, especially with complex or interactive technology, can increase cognitive load due to unfamiliar interfaces and higher multitasking demands (Graesser & D'Mello, 2012; Schrader & Nett, 2018). Adaptive learning platforms, virtual simulations, and other digital media often aim to enhance engagement, yet they can inadvertently increase extraneous load if not well-designed.

For instance, mixed-reality and severe game applications, though innovative, can introduce cognitive challenges if the interfaces are complex or if the required skills exceed students' current capabilities (Schrader & Nett, 2018). Hence, the intersection of cognitive and technological factors is essential for understanding how digital tools impact learning, highlighting the need for instructional strategies that address potential cognitive overload in digital contexts.

Measurement of Cognitive Load

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Measuring cognitive load accurately is critical for assessing how different learning environments and instructional designs affect students. Various methods exist, including psychometric scales (e.g., the Paas Scale), physiological measurements (e.g., pupillometry), and task performance indicators. Each method has strengths and limitations; for instance, the Paas Scale (Paas et al, 2016) provides subjective insight but relies on self-reporting, while physiological tools offer objective data yet require specialized equipment (DeLeeuw & Mayer, 2008; Tzafilkou et al., 2021). The choice of measurement method should align with the study's objectives and context. In this study, combining bibliometric and systematic literature review approaches offers a comprehensive analysis of cognitive load measurement trends, supporting methodological rigour and depth.

Gaps and Rationale for the Study

While extensive research has explored various aspects of cognitive load and its psychological impacts, specific gaps remain. Existing studies often examine cognitive load in isolation without fully integrating psychological factors or evaluating these interactions in digital learning environments. Additionally, prior research has shown inconsistencies in findings regarding the relationship between emotions and cognitive load, particularly in emerging online learning technologies. This study addresses these gaps by identifying trends and examining influential factors in psychological aspects and cognitive load within educational contexts. By synthesizing trends in previous research and assessing the methodological approaches used, this study advances the understanding of educational psychology and cognitive load theory, providing insights that support more effective, student-centred instructional design.

Methodology

Data Source and Search Strategies

The research data source for this study is derived from the Scopus database, chosen for its extensive geographical and thematic coverage, particularly in fields related to psychology, education, and cognitive science (Dindorf et al., 2023). Scopus was selected over other databases like Web of Science and PubMed due to its broad interdisciplinary scope, which aligns with this study's focus on educational psychology and cognitive load. Scopus includes a larger volume of social science research than Web of Science. Unlike PubMed, which primarily focuses on biomedical literature, Scopus offers a more comprehensive representation of educational studies. This makes it an optimal choice for capturing the trends and patterns relevant to this research.

The search strategy included specific terms and Boolean operators to ensure comprehensive coverage. The primary search terms were "Psychological" AND "Cognitive Load" AND "Education," with the query structured as follows: (TITLE-ABS-KEY ("Psychological") AND TITLE-ABS-KEY ("Cognitive Load") AND TITLE-ABS-KEY (education)) AND PUBYEAR > 1991 AND PUBYEAR < 2024. This combination of keywords was refined through initial exploratory searches, testing synonyms and related terms to confirm relevance. Terms that did not contribute additional relevant results, such as synonyms not commonly used in academic literature, were excluded to maintain focus. Only articles published up to 2023 were included, with no restrictions on the initial publication date to capture the entire historical development of the research area.

Research Design and Data Analysis

This study employs a mixed-methods approach that integrates quantitative and qualitative components, providing a multifaceted topic analysis (Creswell, 1999). The quantitative aspect consists of a bibliometric analysis, while the qualitative aspect involves a systematic literature review. Together, these methods enable a comprehensive examination of trends, factors, and research gaps in studying cognitive load and psychology in educational contexts.

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Bibliometric Analysis

Bibliometric analysis, known for its effectiveness in identifying research patterns, provides statistical insights into the structure and evolution of a research field (Donthu et al., 2021). This study uses bibliometric analysis to evaluate patterns and trends in publications related to cognitive load and psychology within education. Data were retrieved from Scopus on July 8, 2024, resulting in 115 documents. Following metadata compliance checks, 113 papers were retained for analysis, as shown in Table 1 below.

Table 1. Completeness of bibliographic metadata

MD	Description	MC	Missing %	Status
AU	Author	0	00.00	Excellent
DT	Document Type	0	00.00	Excellent
SO	Journal	0	00.00	Excellent
LA	Language	0	00.00	Excellent
PY	Publication Year	0	00.00	Excellent
TI	Title	0	00.00	Excellent
TC	Total Citation	0	00.00	Excellent
AB	Abstract	2	0,09513889	Good
C1	Affiliation	2	0,09513889	Good
DI	DOI	6	05.31	Good
RP	Corresponding Author	22	19.47	Acceptable
ID	Keywords Plus	23	20.35	Poor
DE	Keywords	35	30.97	Poor
CR	Cited References	113	100.00.00	Completely missing
WC	Science Categories	113	100.00.00	Completely missing

MD: Metadata; MC: Missing Count

The bibliometric analysis was conducted using R Studio and the Biblioshiny package, facilitating the processing and visualization of citation patterns, co-authorship networks, and research trends. Metrics such as the h-index, g-index, and m-index were calculated to assess the impact and relevance of key articles and authors. Each metric was chosen for its ability to capture different aspects of research impact; for example, the h-index balances publication quantity and citation quality, while the g-index places more weight on highly cited articles, allowing a nuanced view of academic influence. Thresholds for these metrics were determined based on significance in the field, with higher values indicating greater impact.

Systematic Literature Review

The systematic literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to enhance transparency and reproducibility (Page et al., 2021). This process included several stages:

1. Identification: Initial searches in Scopus generated 115 records, of which 113 met the metadata requirements after preliminary screening. Articles not meeting criteria (e.g., publication stage "in press") were excluded.

2. Screening: Titles and abstracts were reviewed based on predefined inclusion criteria: relevance to cognitive load, psychological factors in education, and publication in peer-reviewed

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journals. Exclusion criteria included non-journal articles and conference papers irrelevant to the study's aims.

3. Eligibility: The remaining studies were assessed for full-text eligibility. Studies lacking robust methodological frameworks or not addressing key research themes were excluded.

4. Inclusion: Ultimately, 42 studies were included for in-depth analysis. These studies were categorized according to thematic relevance, with particular attention to psychological and cognitive load factors and methodological rigour.

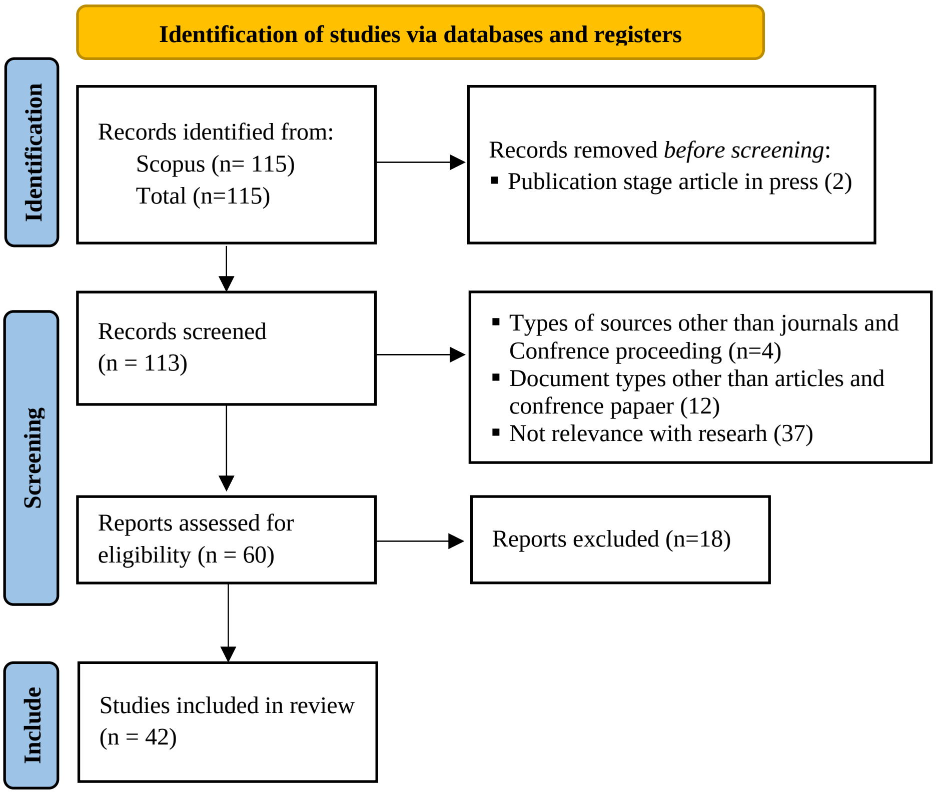

Figure 1. PRISMA Flow Diagram of Study Selection Process

Results

Descriptive Analysis: Evolution of Publications and the Most Globally Cited Articles

The evolution of scientific publications is a crucial indicator of research trends and expanding knowledge within a particular field. Figure 2 illustrates the number of articles published annually from 1990 to 2024 on psychology and cognitive load in education. This data provides valuable insights into research activity and the growing interest among scholars over the years.

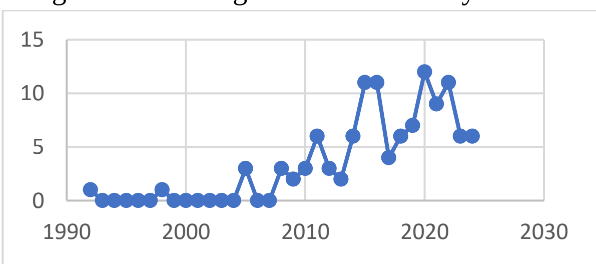

Figure 2. Annual scientific production

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The graph in Figure 2 demonstrates a fluctuating trend in the number of publications, which can be contextualized by examining external factors such as technological advancements, global events, and shifts in educational policy. The period between 1990 and 2005, characterized by minimal publication activity, reflects a time when cognitive load theory and psychological aspects in education were relatively nascent topics with limited attention from the academic community. However, around 2005, a notable increase in publications occurred, possibly influenced by advances in neuroscience and educational psychology, which brought more attention to cognitive factors in learning.

A further breakdown into three-time frames—pre-2005, 2005-2015, and post-2015—highlights distinct shifts in research interest: Pre-2005, research activity was minimal, with fewer than five publications per year, indicating limited recognition of cognitive load as a significant research area, 2005-2015, This period saw gradual growth, with publications peaking at 11 in 2014 and 2015. This increase aligns with the expansion of digital learning technologies, which likely prompted more studies examining the cognitive challenges these technologies introduced. Post-2015, the field peaked in 2020, with 12 publications, coinciding with the surge in online learning due to the COVID-19 pandemic, which emphasized the importance of cognitive load management in remote education. However, post-2020, a slight decline was observed, possibly due to shifting research priorities or saturation in specific study areas.

To enhance the analysis, statistical techniques such as linear regression or trend analysis could be applied to confirm the significance of these observed patterns over time. This approach would help establish whether the fluctuations are statistically meaningful or part of a broader trend in educational psychology research.

Citation Analysis and Publication Impact

The distribution of publication numbers and citation counts across years provides insight into the recognition and impact of research in cognitive load and educational psychology. Table 2 below presents the mean citations per year (MeanTCperYear) from 1992 to 2024.

Table 2. Average citations per year

Year	MTCA	N	MTCY	Year	MTCA	N	MTCY
1992	464,00	1	14,06	2015	34,45	11	3,45
1998	2,00	1	0,07	2016	31,91	11	3,55
2005	38,00	3	1,90	2017	28,00	4	3,50
2008	125,67	3	7,39	2018	12,67	6	1,81
2009	71,00	2	4,44	2019	16,57	7	2,76
2010	51,33	3	3,42	2020	10,83	12	2,17
2011	47,00	6	3,36	2021	46,00	9	11,50
2012	74,33	3	5,72	2022	4,73	11	1,58
2013	10,50	2	0,88	2023	2,33	6	1,17
2014	56,83	6	5,17	2024	0,17	6	0,17

MTCA: Mean TC per Art; MTCY: Mean TC per Year

The citation data reveals that specific years witnessed spikes in mean citations per year, reflecting the presence of highly impactful publications. For instance: 1992, with a mean citation of 14.06 per year, this early publication likely introduced foundational ideas that continued to influence subsequent studies, 2008-2012, A period marked by consistently high citation rates, possibly due to landmark studies that addressed pressing issues in cognitive load, particularly as digital learning began

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to rise in prominence, 2021, An unexpected peak with an average of 11.50 citations per year, possibly reflecting increased interest in cognitive load research during the COVID-19 pandemic as educational systems worldwide shifted to online learning models.

The decline in mean citations from 2022 onward may indicate that recent publications have not established significant academic influence, typical for newer studies still gaining traction in the scholarly community. These fluctuations could also reflect shifts in academic focus or a saturation point in specific research areas within cognitive load theory.

Key Influential Publications and Emerging Trends

A closer examination of the most globally cited articles reveals their high impact due to groundbreaking contributions that filled research gaps or introduced innovative methodologies. For example, highly cited works from 2008-2012 provided critical insights into cognitive load theory's application in digital and online education contexts, bridging knowledge from cognitive psychology to practical educational interventions.

Emerging trends in recent publications focus on adaptive learning technologies, the role of emotions in online learning, and the integration of cognitive load management strategies in digital platforms. Keyword co-occurrence analysis indicates that terms like "adaptive learning," "emotional regulation," and "technology acceptance" have gained prominence in recent years, suggesting a forward-looking trajectory in the field. These emerging themes align with current educational priorities, particularly in optimizing learning technologies to enhance student engagement and reduce cognitive overload.

Methodological Rigor and Bibliometric Techniques

This study utilized several bibliometric techniques, including the h-index, g-index, and keyword co-occurrence analysis, to measure research impact and identify core thematic areas. For example, the h-index provides a balanced view of publication impact by considering quantity and quality, while the g-index emphasizes highly cited works. Including keyword co-occurrence analysis aids in visualizing emerging research clusters, offering a comprehensive picture of the field's evolution and potential future directions.

The fluctuating trends observed in publication counts and citation patterns over time reflect the dynamic nature of research in cognitive load and educational psychology. While external factors such as technological shifts and global events, notably the COVID-19 pandemic, have influenced these patterns, the sustained interest in this field underscores its relevance. The recent emphasis on digital and adaptive learning points toward a future where cognitive load theory continues to inform practical educational strategies, especially in managing cognitive demands in technologically enhanced learning environments.

Citation Source Analysis and Local Impact

The frequency of citations is strongly influenced by the reputation of the journals publishing the articles. Journals with high reputations attract a larger readership, leading to higher citation rates. Several factors contribute to the journal's reputation, including rigorous peer-review processes, inclusion in prestigious indexing databases (such as Scopus and Web of Science), and consistently high historical citation metrics. Open-access availability can also boost readership and citation frequency, making content more accessible to a broader audience.

Figure 3 and Table 3 present the most relevant sources within this field, highlighting journals that publish frequently cited articles in psychology and cognitive load in education.

Figure 3 shows that Medical Education is the leading journal in terms of document count, underscoring its central role in this research area. This prominence is attributed to the journal's high impact factor, extensive topic coverage, and solid editorial standards. Advances in Health Sciences Education and

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Medical Teachers also play significant roles, focusing on educational methodologies, curriculum innovations, and instructional strategies in health sciences. These journals are instrumental in shaping educational practices in healthcare, reflecting the growing intersection of health sciences and educational psychology.

Table 3 provides the leading journals' vital bibliometric metrics—h-index, g-index, m-index, and total citations (TC). Each metric offers distinct insights into journal impact: h-index measures the number of articles with at least h citations, providing a balanced view of publication quantity and quality. The g-index emphasizes highly cited works, reflecting the cumulative impact of top publications, and the m-index offers a time-normalized h-index that is useful for comparing journals established in different periods.

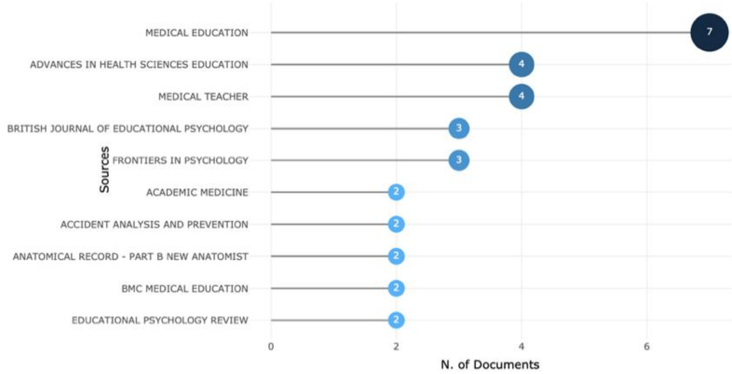

Figure 3. Most relevant sources

Figure 4 provides a clearer view of this field's research trends and principal focuses. The journal Medical Education stands out with the most documents, indicating its status as a central reference and primary source on this research topic. This prominence is attributed to factors such as the journal's esteemed reputation, extensive coverage of issues, or the high quality of its published research. Advances in Health Sciences Education and Medical Teacher also play significant roles, underscoring their substantial contributions to the literature on health education. Their importance reflects a focus on educational methodologies, innovations in teaching, and learning within the health sciences.

British Journal of Educational Psychology and Frontiers in Psychology contribute from the perspective of psychology journals. These publications demonstrate that psychological aspects of education receive considerable attention, with research concentrating on psychological factors related to learning and teaching, such as motivation, cognition, and social interaction. In contrast, journals such as Academic Medicine, Accident Analysis and Prevention, Anatomical Record-Part B New Anatomist, BMC Medical Education, and Educational Psychology Review each have a lesser contribution than the significant journals. Nonetheless, their presence indicates diverse topics and approaches in medical and psychological education research.

Table 3. Source Local Impact

Source	h_index	g_index	m_index	TC
Medical Education	7	7	0,5	670
Advances in Health Sciences Education	4	4	0,4	181
Medical Teacher	4	4	0,444	130
British Journal of Educational Psychology	3	3	0,091	491
Academic Medicine	2	2	0,2	89

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Source	h_index	g_index	m_index	TC
Accident Analysis and Prevention	2	2	0,143	12
Anatomical Record - Part B New Anatomist	2	2	0,1	114
BMC Medical Education	2	2	0,167	77
Educational Psychology Review	2	2	0,4	309
Frontiers in Psychology	2	3	0,5	17

Among these, Medical Education exhibits the highest h-index and total citations, affirming its influence in the field. Its publications on instructional methods, medical education innovations, and professional development are frequently referenced, establishing it as a pivotal resource. Advances in Health Sciences Education and Medical Teacher also demonstrate robust metrics, underscoring their roles in advancing health education methodologies.

British Journal of Educational Psychology and Frontiers in Psychology focus on the psychological aspects of education. Research published in these journals often explores motivation, cognition, and social interaction within educational contexts, contributing essential insights into how psychological factors influence learning. Academic Medicine primarily addresses professional development and instructional design within medical education, presenting research crucial for developing healthcare educational frameworks.

Accident Analysis and Prevention and Anatomical Record - Part B New Anatomists are more specialized, focusing on accident prevention and anatomical education. Although their citation counts are lower, these journals contribute valuable perspectives to interdisciplinary studies connecting cognitive load, safety, and anatomy education. BMC Medical Education and Educational Psychology Review offer open-access articles that enhance accessibility, allowing broader dissemination of research findings. This accessibility likely contributes to their citation frequency, as researchers and practitioners can freely access and reference their content.

An analysis of citation longevity reveals that some of the older articles in Medical Education and the British Journal of Educational Psychology are influential, indicating that foundational studies in these journals retain relevance. In contrast, journals like Frontiers in Psychology, which publish newer research, reflect emerging themes and current trends, indicating a gradual shift towards citing recent publications that address evolving educational needs, especially in digital and cognitive load management.

Analyzing local and international collaborations highlights how geographic distribution impacts citation patterns. Collaborative research between institutions in different countries often results in higher citation rates as these studies reach a wider audience. For example, articles from Medical Education with international co-authorship have a broader influence, underscoring the importance of cross-regional research in disseminating knowledge and enhancing journal impact globally.

Collaboration Analysis: Countries and Authors

Analyzing the relationship between authors and countries is crucial for developing a comprehensive understanding of the structure and dynamics of scientific research. This relationship can reveal how patterns of research collaboration evolve. The local impact of authors in the academic world can be assessed through various metrics such as the h-index, g-index, m-index, total citations (TC), and number of publications (NP). These metrics provide insights into the frequency with which an author's work is cited and the extent of its influence. Table 4 illustrates the local impact of several prominent authors based on these metrics.

Table 4. Authors Local Impact

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Author	h_index	g_index	m_index	TC	NP
Mclaughlin K	4	4	0,267	348	4
Dubrowski A	3	3	0,3	118	3
Irby Dm	3	3	0,3	102	3
Khalil Mk	3	3	0,15	135	3
Artino Ar	2	2	0,143	189	2
Coderre S	2	2	0,133	36	2
De Ribaupierre S	2	2	0,2	115	2
Fraser K	2	2	0,154	312	2
Haji Fa	2	2	0,2	115	2
Johnson Te	2	2	0,1	114	2

Based on the data in Table 4, the h-index measures both productivity and the impact of an author's publications. McLaughlin K exhibits the highest h-index, indicating that each of their four publications has been cited at least four times. Other authors demonstrate a more limited influence. The g-index, on the other hand, accounts for the total number of citations in assessing an author's impact. McLaughlin K also holds the highest g-index, suggesting that the publications with the highest citations have a minimum of 16 citations. Other authors show a g-index equivalent to their h-index, reflecting a relatively uniform distribution of citations.

The m-index represents the ratio of the h-index to the duration of the author's career. This metric normalizes the h-index based on career length. Dubrowski A and Irby Dm possess the highest m-index, indicating a relatively high impact within a shorter timeframe. McLaughlin K has an m-index of 0.267, which, while slightly lower, still signifies a notable impact.

Total citations reveal how frequently an author's work has been cited overall. McLaughlin K has the highest total citations (348), demonstrating substantial influence. Fraser K (312) and Artino Ar (189) also have high citation counts, reflecting significant impact despite fewer publications. The number of publications indicates an author's productivity. McLaughlin K and authors with an h-index and g-index of 3 have the highest publication counts. Other authors, such as Artino Ar and Fraser K, have fewer publications but with a substantial impact per publication.

Understanding the geographic distribution of authors contributing to academic publications is crucial for examining the dynamics of international collaboration and the regional influence of research. The country of the corresponding authors, number of articles, percentage of total articles, number of single-author articles (SCP), number of multi-country author articles (MCP), and the percentage of MCP are detailed in Table 5.

Table 5. Corresponding authors countries

Country	Articles	Articles %	SCP	MCP	MCP %
USA	31	27,4	24	7	22,6
China	11	9,7	9	2	18,2
Canada	9	8	5	4	44,4
Australia	7	6,2	4	3	42,9
Germany	5	4,4	5	0	0
United Kingdom	5	4,4	4	1	20
Korea	3	2,7	2	1	33,3
Denmark	2	1,8	2	0	0

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Country	Articles	Articles %	SCP	MCP	MCP %
Iran	2	1,8	2	0	0
Netherlands	2	1,8	1	1	50

The United States predominates in contributions with 31 articles, accounting for 27.4% of the total publications, thereby underscoring its position as a leader in international research. China and Canada also demonstrate substantial contributions, with 11 and 9 articles reflecting a high level of research activity within these nations. Other countries, such as Australia, Germany, and the United Kingdom, exhibit more minor yet significant contributions, with 7, 5, and 5 articles, respectively.

The United States has published 24 SCP (Single Country Publications) articles and 7 MCP (Multi-Country Publications) articles (22.6%), indicating that the majority of research is conducted domestically with some international collaboration. China shows a similar pattern with 9 SCP articles and 2 MCP articles (18.2%). Canada and Australia display a higher proportion of MCP, at 44.4% and 42.9%, respectively, signifying a greater extent of international collaboration. Germany, Denmark, and Iran have no MCP articles focusing on domestic research. The Netherlands exhibits the highest MCP percentage (50%), indicating that half of its contributions involve international collaboration. The percentage of articles provides insight into the extent of each country's contribution to the total publications. The United States, with 27.4%, demonstrates clear dominance. Other nations such as China (9.7%), Canada (8%), and Australia (6.2%) also make significant contributions, highlighting the crucial role of researchers in the global research landscape.

The analysis of the corresponding authors' countries is also associated with a world map that illustrates the geographic distribution of research related to education and psychology based on the number of publications. The map depicts countries in varying intensities of blue, representing the volume of research publications from each country. A darker shade of blue in a country signifies a higher volume of publications or contributions from researchers in that nation.

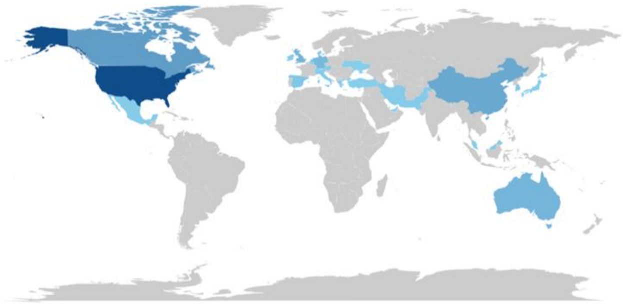

Figure 4. Countries scientific productions

Figure 4 illustrates that the United States is depicted in a deep blue hue, signifying the highest volume of publications or the largest research contributions. China, the United Kingdom, Germany, and Australia are in a darker blue shade, indicating substantial publication output, though not as extensive as that of the United States. Countries such as Canada, India, Japan, South Korea, France, Italy, and Brazil are shown in a medium blue, reflecting considerable research contributions, yet not reaching the level of the group mentioned above. Conversely, nations like Mexico, South Africa, Indonesia, Thailand, Saudi Arabia, and Turkey are marked in a lighter blue, denoting existing research contributions, albeit at a lower scale.

Development of Psychology and Cognitive Load

Citation: Firdaus, T., Amelia, A., Alifiyah, F.L.N., Nahdliyah, A.S., & Fausiyeh, F. (2025). Trends and Effects of Psychological and Cognitive Load in Education. Journal of Education and Learning Reviews, 2 (2), 97-128; DOI: https://doi.org/10.60027/jelr.2025.1084

Citation counts are frequently employed in the academic realm as a metric for evaluating the impact and relevance of research. The subsequent table presents the most commonly cited documents, offering insights into researchers' contributions to their respective fields of study. Table 6 includes total citations, annual average citations, and normalized citations.

Table 6. Most cited document

Paper	DOI	TC	TCY	NTC
Chandler Paul, 1992	10.1111/j.2044-8279.1992.tb01017.x	464	14,06	1,00
Deleeuw Ke, 2008	10.1037/0022-0663.100.1.223	355	20,88	2,82
Makransky G, 2021	10.1007/s10648-020-09586-2	301	75,25	6,54
Fraser K, 2012	10.1111/j.1365-2923.2012.04355.x	213	16,38	2,87
Murphy G, 2016	10.3758/s13423-015-0982-5	144	16,00	4,51
Durning S, 2011	10.1111/j.1365-2923.2011.04053.x	144	10,29	3,06
Holzinger A, 2009	10.1016/j.compedu.2008.08.008	142	8,88	2,00
Naismith Lm, 2015	10.1111/medu.12732	109	10,90	3,16
Moreno R, 2010	10.1017/CBO9780511844744.003	109	7,27	2,12
Fraser K, 2014	10.1378/chest.13-0987	99	9,00	1,74

TC: Total Citation; TCPY: Total Citation per Year; NTC: Normalized TC

Based on the total citations presented in Table 6, the article by Chandler & Sweller (1992) has garnered the highest number of citations, amounting to 464. This article is the earliest work in the table and has maintained a steady accumulation of citations over three decades. Articles by Deleeuw (2008) and Makransky & Petersen (2021) also have a high citation count, with 355 and 301 citations, respectively. Despite Makransky's article being published only in 2021, the number of citations it has received indicates a significant impact in a short period.

The article by Makransky (2021) has the highest annual citation rate, at 75.25, indicating its relevance and substantial impact since publication. The article by Deleeuw (2008) also demonstrates a high annual citation rate of 20.88, reflecting broad acceptance within the academic community. Articles by Fraser (2012) have consistent and notable annual citation rates, at 16.00 and 16.38, respectively.

The article by Makransky (2021) has the highest normalized citation value, at 6.54, indicating that despite being a recent publication, its impact significantly surpasses many other articles. Articles by Fraser (2012) also have high normalized citation values, at 4.51 and 2.87, respectively, underscoring the significant contributions of these researchers. The article by Deleeuw (2008), with a normalized value of 2.82, also demonstrates considerable impact compared to the average citation standards.

The most cited documents are associated with frequently appearing terms in research. Figure 5 presents a word cloud depicting terms frequently appearing in research related to education and psychology. The size of each word represents the frequency or relative importance of the term within the corpus of analyzed research data.

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Figure 5. Wordcloud

The term "Human/Humans" appears prominently, indicating that much research focuses on humans as the primary subjects. "Education/Educational" is a central theme in many studies, as evidenced by the prominence of these terms. "Cognition" significantly emphasizes cognitive processes within the contexts of education and psychology. "Learning" emerges as a critical topic, highlighting a substantial interest in understanding learning processes and methodologies. "Medical Education" is also a heavily researched area, as indicated by the term's prominence. Additionally, "Psychological Theory" constitutes a crucial component in numerous studies.

Other notable terms include "male/female," "teaching," "clinical competence," "adult," and "students/medical student." Furthermore, specific terms such as "cognitive loads" indicate an interest in cognitive load and its impact on learning. "Simulation training" is another term associated with popular methods in medical education. Psychological aspects are also a significant consideration in many studies.

The frequently occurring terms in research significantly influence the issues being discussed. Figure 6 depicts the trends in using various terms in research from 2005 to 2023. Each point on the horizontal axis represents the number of publications using a particular term in a given year, with the size of the circle indicating the frequency or intensity of usage. The graph illustrates specific terms' temporal distribution and popularity in education and psychology research. Each term is represented on the vertical axis, with the years on the horizontal axis.

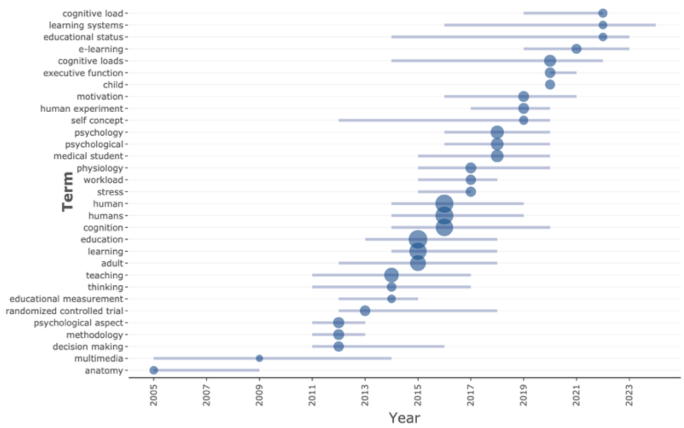

Figure 6. Trend topics

Trend topics refer to research patterns or directions over the past decade. These research trends reveal topics currently receiving significant attention. In 2005, research trends focused solely on anatomy, with a term frequency of 6. In 2009, the focus shifted to multimedia, with a frequency of 5 terms. By 2012, research trends encompassed decision-making (10 terms), methodology (12 terms),

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Journal of Education and Learning Reviews, 2 (2): March-April 2025 ISSN: 3057-0387
Website: https://so19.tci-thaijo.org/index.php/JELS/about

and psychological aspects (13 terms). In 2013, the focus was on randomized controlled trials, with a term frequency of 11. The year 2014 saw a focus on educational measurement (6 terms), thinking (8 terms), and teaching (33 terms). In 2015, the research focus included adults (42 terms), learning (55 terms), and education (70 terms).

In 2016, the trends concentrated on cognition (57 terms), humans (62 terms), and humans (64 terms). The following year, 2017, the focus was on stress (10 terms), workload (10 terms), and physiology (12 terms). In 2018, research trends centred on medical students (20 terms), psychological (20 terms), and psychology (24 terms). In 2019, the focus was on self-concept (7 terms), human experiment (12 terms), and motivation (12 terms). In 2020, the focus shifted to child (9 terms), executive function (11 terms), and cognitive load (17 terms). The trend in 2021 focused on e-learning, with a term frequency of 9. In 2022, the trends included educational status (6 terms), learning systems (6 terms), and cognitive load (7 terms).

Cognitive load, learning systems, executive function, and motivation have significantly increased in recent years. Psychology, medical students, and stress have also demonstrated a high and consistent frequency of use. Terms such as human, cognition, education, and learning have shown stable popularity year after year, reflecting their ongoing relevance in research. Terms like anatomy, multimedia, and decision-making have emerged and gained prominence since 2015.

The graph illustrates how the research focus has shifted over time. Newer terms such as e-learning and multimedia reflect the trend towards digitalization in education. Terms like stress, motivation, and psychological highlight an increasing concern for education's mental health and psychological factors. The rise in technology-related terms indicates how technology has become integral to modern education.

Focusing on specific learners, such as medical students and children, indicates in-depth research on particular population groups. Research on self-concept and motivation shows a focus on internal aspects of learning. Topic trends align with co-occurrence in research, as topics frequently appearing in an article often indicate a relationship through co-occurrence. Co-occurrence in research helps identify and understand the relationships between various issues, reflecting the development of research trends and the interconnections between different concepts and approaches, as shown in Figure 7.

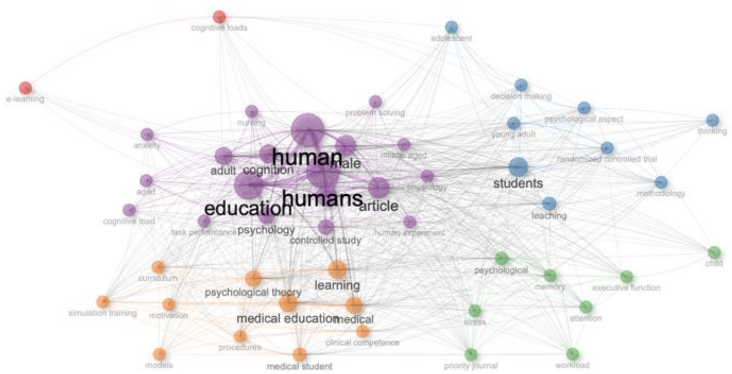

Figure 7. Co-occurrences network

Based on the results shown in Figure 7, five clusters were identified. Each cluster is organized by color-coded categorization. The first cluster, coloured red, consists of 2 items. The second cluster, coloured blue, comprises nine items. The third cluster, coloured green, contains eight items. The fourth cluster, coloured purple, includes 19 items. Finally, the fifth cluster, coloured orange, consists of 11 items.

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Some prominent key topics include humans, education, psychology, and learning. The size of each node indicates the frequency of these topics in publications, while the thickness of the lines denotes the strength of the relationships between topics. The primary cluster in the co-occurrence network, represented by the purple cluster, encompasses topics such as humans, education, psychology, and learning, illustrating the close interrelationship among these subjects. The nodes for humans and education are particularly prominent, indicating that research on humans and education is central to this network. The blue cluster highlights topics such as students, teaching, and young adults, signifying a research focus on education and teaching for younger age groups. The green cluster involves topics such as psychology, memory, and attention, demonstrating a strong connection between education and psychological aspects.

Analyzing research network visualization and citation statistics can help better understand how research trends influence specific topics. Central topics like humans and education significantly impact and are often associated with increased citations. Fluctuations in citation counts also reflect the dynamics and relevance of research in these fields. Understanding these trends is crucial for future publication strategies and research planning.

Systematic Literature Review

Integrating online education and technology in learning environments has gained significant traction, especially following the COVID-19 pandemic, accelerating the shift toward digital learning. A critical aspect of this shift is cognitive load, which refers to the mental effort required to process information. Cognitive load is categorized into intrinsic, extraneous, and germane loads, each impacting the effectiveness of learning differently. This systematic literature review aims to evaluate studies examining the relationships between cognitive load, psychological factors, and technology in educational contexts.

Numerous studies explore how different types of cognitive load—intrinsic, extraneous, and germane—impact learning outcomes. For example, DeLeeuw & Mayer (2008) used self-report scales to measure mental effort, revealing that different cognitive load components can be isolated to optimize instructional design. Chandler & Sweller (1992) emphasize reducing extraneous load through integrated instructional formats, a finding supported in subsequent studies on instructional design. These studies underscore the importance of minimizing unnecessary cognitive load to enhance learning efficiency.

Psychological factors, particularly emotions, motivation, and mental resilience, play significant roles in students' cognitive load management. For instance, Fraser et al. (2014) highlighted that unexpected emotional stressors, such as patient death during medical training simulations, can elevate cognitive load and negatively affect learning outcomes. Tzafilkou et al. (2021) found that boredom and anxiety strongly predict cognitive load in remote learning settings, impacting students' acceptance and engagement in online education.

The increased use of digital platforms has introduced new complexities in managing cognitive load. Studies such as Holzinger et al. (2009), which examined the HAEMOSIM simulator's impact, suggest that simulation tools significantly enhance learning performance by balancing cognitive demands when combined with structured support. Cai & Yang (2020) developed an interactive virtual experiment platform, finding that immersive technology can increase student engagement without overwhelming cognitive resources. These findings highlight digital tools' potential benefits and limitations in cognitive load management.

Effective instructional design is central to managing cognitive load in educational settings. Naismith et al. (2015) explored how cognitive load components influence procedural training outcomes, demonstrating that carefully calibrated instructional design can enhance the retention of complex skills. Khalil et al. (2010), through the use of Likert scales and paired t-tests, found that decreasing extraneous

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cognitive load directly supports improved learning outcomes in medical training, further validating the principles of cognitive load theory.

Table 7. Review Analysis

title	sample size	Methods Used	Key finding
A1_(Szulewski et al., 2017).pdf	32 participant	Experimental design	A strong positive correlation exists between the Pupillary Change Index (PCI) and the Paas scale.
A10_(Atiomo et al., 2024).pdf	41 students	Data analysis	students perceiving low mental effort, low extraneous cognitive load, and high self-perceived learning or germane cognitive load
A11_(Khalil et al., 2010).pdf	80 participant	a Likert scale and a paired t-test	Decreasing extraneous cognitive load, ultimately enhancing the learning process for students
A12_(Tang et al., 2022).pdf	60 participant	Randomized experiment	Immersion in a high-immersion environment increased the sense of presence and decreased extraneous cognitive load compared to viewing content on an iPad.
A13_(Rashid et al., 2022).pdf	16 student, 7 teacher	interviews and focus group discussions	Students are at risk of academic failure before the first significant assessment, allowing for early intervention and prevention of academic setbacks.
A14_(Klein et al., 2019).pdf	98 medical student	One-factorial design with three groups and presenting cases	Significant learning progress in all conditions. Neither prompting procedure improved the learning outcomes beyond the level
A15_(Fraser et al., 2012).pdf	84 medical student	Factor analysis	Increased invigoration and reduced tranquillity during simulation training were associated with increased cognitive load
A16_(Haji, Khan, et al., 2015).pdf	28 participants	Two-way mixed ANOVA	Significant improvement in knot-tying performance during simulation training
A17_(Holzinger et al., 2009).pdf	92 participant	pretest and posttest 3x2 design	combination of additional support and the HAEMOdynamics SIMulator (HAEMOSIM) yielded significantly higher learning performance compared to conventional
A18_(Huang et al., 2020).pdf	38 collage student	T -Test and one-way ANOVA	the sequence of watching videos did not impact the learning outcomes significantly
A19_(Costa et al., 2019).pdf	19 student	Mann-Whitney and Kruskal-Wallis tests	the use and acceptance of technologies by professors in a higher education institution
A2_(Ji et al., 2023).pdf	31 participant	Experimental design	cognitive load of the basic level category for Chinese English learners was the lowest compared

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title	sample size	Methods Used	Key finding
			to the superordinate and subordinate categories
A20_(Lee et al., 2024).pdf	20 instructors	Mixed Model ANOVAs	student engagement cues significantly enhanced instructors' ability to monitor students' engagement with greater accuracy
A21_(Joksimovic et al., 2014).pdf	1747 messages of students'	Linguistic analysis	Linguistic proxies of increased cognitive load have unique representation
A23_(Haji, Rojas, et al., 2015).pdf	First and second-year undergraduate medical students (n = 8)	psychophysiological methods	novices demonstrated higher mental
A23_(Hwang et al., 2011).pdf	122 participants.	online text reconstruction program, and partial Least Squares (PLS)	somatic anxiety was not significantly related to students' interest in playing the game
A24_(Murata & Suzuki, 2015).pdf	5 participant	artifact robust estimation method	the presented method significantly estimated cognitive load against body motion
A25_(Naismith et al., 2015).pdf	38 medical residents	the Paas Cognitive Load Scale, the NASA TLX, and a six-item cognitive load component (CLC)	Intrinsic cognitive load was found to align with mental effort, mental demand, and task difficulty and complexity,
A26_(Tzafilkou et al., 2021).pdf	116 individuals.	The Partial Least Squares Structural Equation Modeling (PLS-SEM)	Negative emotions of boredom and cognitive load significantly predict students' acceptance of remote learning components
A27_(Han et al., 2022).pdf	11 male and 8 female students	Linear growth models	students needed more than 4 weeks and only one week of training to feel comfortable with VR technology
A28_(Choi & Lee, 2022).pdf	800 learners	Cognitive Load Scale (CLS),	Germane cognitive load was significantly related to final exam scores
A29_(Russ et al., 2018).pdf	50 medical students	randomly assigned to four experimental	A significant relationship between acute stress and impaired technical performance in medical students
A3_(Brunzini et al., 2022).pdf	20 students	multiple measurement techniques	The MR simulations successfully enhanced the realism of the training without generating cognitive overload
A30_(Mohan et al., 2016).pdf	366 physicians	Randomization and blinding	Night Shift facilitated analogical encoding and narrative engagement
A31_(Andersen & Makransky, 2021).pdf	509 students	Partial Credit Model (PCM) for Item Response Theory (IRT)	The Multidimensional Cognitive Load Scale for Physical and Online Lectures (MCLS-POL) goes beyond the traditional Cognitive Load Scale (CLS) by expanding the extraneous load (EL)

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title	sample size	Methods Used	Key finding
A32_(Güth & van Vorst, 2024).pdf	217 chemistry student	experimental	The congruence between the choice options and the student's characteristics is more crucial for satisfaction
A33_(Toma & Vahrenhold, 2018).pdf	15 male and 6 female participants	A combination of quantitative and qualitative approaches	Understanding learning barriers faced by students in different environments
A34_(Young et al., 2016).pdf	52 students	design with two explanatory variables	Illness script maturity was more crucial in determining handover accuracy and cognitive load than case complexity.
A4_(Ureña et al., 2020).pdf	49 preschool children	Assessing self-regulation (SR)	Physical exercise with cognitive involvement improves self-regulation and cognitive control in preschoolers
A5_(Athilingam et al., 2016).pdf	10 participants	Developmental Project	Heart failure educational modules in a mobile platform significantly improved patients' self-efficacy and confidence in using the app for HF education
A5_(Avgerinou & Tolmie, 2020).pdf	95 children	experimental-correlational design	Inhibitory control uniquely contributed to performance in counterintuitive fractions and decimals only under conditions of high cognitive load
A6_(Werner et al., 2013).pdf	12 students	randomized, controlled, prospective cross-over design	Communication training for advanced medical students significantly improved the information recall of medical laypersons
A7_(DeLeeuw & Mayer, 2008).pdf	155 students in Experiment 1, 99 in Experiment 2, and 56 in another study.	Self-report scales for mental effort ratings	Understanding and measuring cognitive load accurately to enhance instructional design and learning outcomes.
A8_(Cai & Yang, 2020).pdf	66 students	development of a virtual experiment platform based on Blender and HTML5	The application of the interactive virtual experiment platform based on Blender and HTML5 technology enhances the immersion and intelligence of the experimental process
A9_(Kadir et al., 2020).pdf	427 participants	cluster-level assignment design	The Dual-Approach Instruction (DAI) intervention significantly improved students' achievement in complex problem-solving and positively impacted six motivational attributes
(Chandler & Sweller, 1992).pdf	20 subjects	Conducted to investigate and compare conventional and integrated formats in areas	The importance of reducing extraneous cognitive load through integrated instructional design.

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title	sample size	Methods Used	Key finding
(DeLeeuw & Mayer, 2008).pdf	155 college students	self-report scales	different measures can tap different aspects of cognitive load
(Durning et al., 2011).pdf	25 board-certified internists	A constant-comparative approach	Contextual factors significantly influence clinical reasoning performance, with experts being aware of this influence
(Fraser et al., 2012).pdf	84 medical students.	factor analysis	Two principal components of emotion, invigoration and tranquillity, were linked to cognitive load and diagnostic performance.
(Fraser et al., 2014).pdf	116 final-year medical students	Prospective randomized	The emotional impact of unexpected patient death during simulation training significantly influenced cognitive load and learning outcomes
(Holzinger et al., 2009).pdf	92 participants	compared learning pretest and posttest 3x2 design	The combination of video instruction and subsequent use of the HAEMOdynamics SIMulator (HAEMOSIM)
(Naismith et al., 2015).pdf	38 medical residents	paired-sample t-tests, independent-sample t-tests, ANOVA, Bonferroni correction, and Pearson correlations	Cognitive load components and their impact on procedural training outcomes

Cognitive Load and Instructional Media

Instructional videos have become one of online education's most widely used tools. Research shows that the video's complexity can significantly affect cognitive load. In the context of instructional media, cognitive load can be categorized into three main types: intrinsic, extraneous, and germane, each of which has a distinct impact on learning.

Intrinsic Cognitive Load is a type of cognitive load inherent to the material itself, determined by the complexity of the content and the learner’s prior knowledge. For example, learning complex procedures like surgical techniques or diagnostic processes in medical education generates a high intrinsic load due to the intricacy of the tasks involved. Instructional media, such as videos or interactive modules, must be designed to match the learner's skill level, balancing content complexity to avoid overwhelming the cognitive capacity.

Extraneous load refers to the mental effort exerted on processing information that does not directly contribute to learning. This type of load can be minimized through clear and straightforward instructional design. For example, simple, well-structured videos free from unnecessary details help reduce extraneous cognitive load, allowing learners to focus on core content. When students watch complex videos followed by simpler ones, they allocate more cognitive resources to understand the challenging content, which can improve overall comprehension and retention.

Germane load is associated with the mental effort toward schema construction and integrating new information into long-term memory. Instructional media encouraging active engagement, such as quizzes embedded in videos or interactive exercises, can increase germane load. For instance, when students apply newly learned concepts in simulations, they are more likely to develop and reinforce mental schemas, enhancing learning effectiveness.

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Simulations, particularly in medical education, enhance learning outcomes by providing a controlled environment where students can practice real-life scenarios without real-world risks. Studies indicate that interactive simulations like HAEMOSIM, developed for medical training, help manage the cognitive load by offering practical, hands-on experiences that reinforce learning. Simulations that mirror real-life situations reduce extraneous cognitive load by providing structured, guided tasks and promote germane cognitive load through active problem-solving and skill practice.

Moreover, combining simulations with instructional videos is more effective than traditional text-based methods. The visual and interactive components of simulations complement the instructional content in videos, creating a cohesive learning experience that supports cognitive processing and knowledge retention. Such an approach allows students to gradually build on their knowledge and skills, moving from understanding basic concepts in videos to applying them in simulated environments, ultimately enhancing both theoretical understanding and practical competence.

The Impact of Cognitive Load on Performance and Motivation

Cognitive load refers to the mental effort required to process information and is a crucial consideration in instructional design. Cognitive load is generally categorized into three types: intrinsic, extraneous, and germane, each of which affects learning outcomes differently.

Intrinsic Cognitive Load is inherent to the complexity of the learning material itself and depends on the nature of the content and the learner’s prior knowledge. For example, subjects like physics or chemistry often have a high intrinsic load due to the complex concepts involved, requiring students to engage deeply with the material. Instructional strategies that scaffold content or break it down into smaller, manageable parts can help learners manage intrinsic load effectively.

Extraneous load arises from how information is presented rather than the content itself. Poorly designed instructional materials, such as cluttered visuals or complex language, can increase this load unnecessarily. Minimizing extraneous cognitive load allows students to focus on essential information without distractions, enhancing their learning efficiency. Well-designed digital tools, such as clean and interactive interfaces, can reduce extraneous load by simplifying navigation and emphasizing critical content.

Germane load is related to the mental resources devoted to constructing and automating schemas or cognitive models. Instructional strategies encouraging active engagement, such as quizzes or interactive exercises, can enhance germane load by promoting schema formation. For instance, activities that require students to apply new knowledge in practical contexts help them integrate and retain information in long-term memory.

Research shows that innovative instructional strategies, such as digital interactive technology, can effectively reduce extraneous cognitive load compared to traditional paper-based methods. For example, well-designed computer-based learning tools allow students to process information more efficiently by reducing distractions and directing their attention to critical aspects of the material. This focus on essential content enables learners to devote more cognitive resources to understanding core concepts, ultimately enhancing academic performance. Simulations and digital platforms incorporating interactive elements can help learners manage the intrinsic load by breaking complex information into digestible units. These digital approaches provide structured guidance and opportunities for students to engage in active learning, which is instrumental in developing their understanding and skills.

Beyond cognitive load, psychological factors like motivation are fundamental to successful learning. Motivation enhances engagement, drives persistence, and fosters deeper involvement in the learning process. Effective learning strategies not only improve task performance but also positively impact motivational attributes, including:

1. Self-Regulation: Encouraging students to monitor and control their learning process, enhancing their ability to manage time and effort.

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2. Engagement: Increasing students' active participation is essential for maintaining attention and involvement in complex tasks.

3. Sense of Competence: Building students' confidence in their abilities, making them more likely to tackle challenging tasks.

4. Task Goal Orientation: Focusing on learning goals rather than merely completing tasks fosters a more profound commitment to understanding the material.

5. Educational Aspirations: Strengthening students' desire to pursue further education, particularly in challenging fields.

6. Career Aspirations in Science: Cultivating interest in scientific careers by making learning experiences more relevant and motivating.

These motivational factors reinforce students' willingness to engage with instructional content actively and persist in achieving learning objectives. For instance, a competent and engaged student is more likely to persevere in challenging subjects, especially when instructional strategies effectively manage cognitive load and encourage schema formation.

Measuring Cognitive Load: Physiology and Psychometrics

Cognitive load, a crucial factor in learning effectiveness, can be measured using various methods, primarily physiological and psychometric techniques. Each method offers unique advantages and limitations depending on the use context, such as high-stakes assessments or real-time monitoring in virtual learning environments.

Physiological Methods like pupillometry measure cognitive load by tracking changes in pupil diameter. Pupillary response is a reliable indicator of mental effort, as pupil dilation often increases with cognitive demands. This method is advantageous in high-stakes or real-time monitoring contexts, such as virtual reality (VR) environments, where it provides immediate and objective feedback on a learner's cognitive load without interrupting the learning process. However, physiological methods require specialized equipment and controlled conditions, limiting their applicability in more typical educational settings. Advantages are objective and non-intrusive, suitable for real-time assessments, especially in dynamic and immersive environments. Limitations require specialized equipment and controlled settings, which may not be feasible in traditional classrooms or remote learning environments.

Psychometric Methods like the Paas scale rely on subjective assessments where learners rate their perceived mental effort. This scale is widely used in research due to its simplicity and ease of administration, making it suitable for various learning environments, including classroom-based assessments and online lectures. However, the Paas scale may be susceptible to individual biases and inconsistencies because it relies on self-reporting. In high-stakes situations where accuracy is critical, such as licensing exams, subjective methods may lack the objectivity to assess cognitive load reliably. The advantages of this research are easy to administer, cost-effective, and adaptable to various learning contexts. Limitations are subjective and potentially biased, making it less reliable in high-stakes assessments where accuracy is critical.

Studies indicate a strong positive correlation between physiological and psychometric measures, suggesting that both methods can effectively capture cognitive load, though each may best suit specific contexts. For instance, pupillometry might be ideal for real-time cognitive load monitoring in VR training environments. At the same time, the Paas scale could be more practical in traditional educational settings where immediate measurement is not necessary.

In addition to pupillometry and the Paas scale, other tools have been developed to capture cognitive load in educational contexts. For instance, the Multidimensional Cognitive Load Scale for Physical and Online Lectures (MCLS-POL) has been validated as a reliable tool for measuring cognitive

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load across diverse higher education settings. The MCLS-POL extends beyond single-dimension assessments by measuring multiple cognitive load facets, allowing for a more comprehensive understanding of mental effort in complex learning environments. This multidimensional approach is precious for online and hybrid education, where cognitive load dynamics may differ from traditional classroom settings. The advantages of MCLS-POL are that it provides a nuanced measurement across different types of cognitive load (intrinsic, extraneous, and germane) and is validated for use in physical and online lectures. Limitations are more complex to administer and interpret than single-dimensional scales, requiring specific training or experience to use effectively.

Accurate measurement of cognitive load is essential for understanding how instructional designs impact learning outcomes and developing interventions tailored to specific educational contexts. Physiological methods like pupillometry and psychometric methods like the Paas scale each have distinct applications based on their strengths and limitations. Meanwhile, tools like the MCLS-POL offer a multidimensional approach, contributing to a richer understanding of cognitive load in increasingly diverse educational settings. Educators and researchers can more effectively assess and manage the cognitive load by selecting appropriate measurement methods based on context-optimizing learning strategies for various environments.

The Role of Emotions in Distance Learning

Students' emotions, particularly negative emotions such as boredom and anxiety, significantly impact the learning experience. Negative emotions in the context of distance learning can increase cognitive load and decrease learning effectiveness. Research shows that boredom can distract students and reduce their learning motivation. Increased cognitive load due to negative emotions can hinder students' ability to process information efficiently and diminish the absorption of learning materials.

Emotions also influence students' acceptance of technology. Studies on using technologies such as Moodle, Facebook, and YouTube in higher education indicate that perceived usefulness and ease of use are critical determinants of technology acceptance. However, negative emotions can lower perceptions of usefulness and ease of use, thereby hindering the adoption of these technologies in learning. Therefore, managing students' emotions in distance learning is crucial for enhancing technology acceptance and learning effectiveness.

Technology and Learning Effectiveness

Technology has become an integral part of modern education. Learning platforms like Moodle and social media like Facebook and YouTube have become essential tools for online learning. Studies show that these technologies are generally well-received by students and professors, with perceived usefulness and ease of use being critical factors in their acceptance. These technologies enable the delivery of more interactive and engaging content, enhancing student engagement and reinforcing learning.

The use of technology in learning also faces challenges, one of which is managing cognitive load. Although technology can increase realism and engagement, excessive or inappropriate use can increase cognitive load and reduce learning effectiveness. Mixed Reality (MR) simulations in medical training have been shown to improve student stress without increasing perceived workload, which can lead to excessive cognitive load. Therefore, it is essential to design balanced and effective use of technology, considering students' needs and capacities.

Discussion

Research Patterns and Trends

The annual citation counts of cognitive load theory and educational psychology publications show fluctuating trends, with notable periods of increase and decrease. This variation can be attributed

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to multiple factors, such as advancements in instructional design, technological shifts, and changing priorities within educational research. Aligning these trends with established research, like Sweller's (2010) Cognitive Load Theory and Mayer's (2008) work on multimedia learning, provides a deeper understanding of the evolving focus in this field.

For instance, as digital learning tools and multimedia have become more prevalent, researchers have increasingly examined extraneous cognitive load—unnecessary mental effort due to poorly designed instructional materials. This focus reflects the influence of Mayer's principles for reducing cognitive load through well-designed multimedia instruction. Furthermore, the recent increase in publications discussing "e-learning" and "adaptive learning" tools illustrates a response to the growing demand for technology-supported education, particularly during the COVID-19 pandemic.

Drivers of Citation Fluctuations

Several drivers influence the observed fluctuations in citation counts:

1. Technological Advancements: Innovations in educational technology, such as simulations, adaptive learning platforms, and immersive virtual environments, have stimulated new research interest. These tools are recognized for their potential to manage cognitive load by providing interactive, real-time feedback (Makransky & Mayer, 2021).
2. Evolution in Instructional Design: Advances in instructional design methodologies, focusing on reducing extraneous cognitive load, have increased citations. For example, research that applies Mayer's principles of multimedia learning has gained traction as educators seek strategies to enhance engagement and reduce distractions in digital formats.
3. Global Events: The COVID-19 pandemic accelerated the shift to online education, sparking increased research on cognitive load in virtual settings. This period saw a peak in publications exploring the psychological and cognitive challenges of remote learning environments, emphasising the role of technology in maintaining educational continuity.

Geographical Analysis of Research Contributions

The United States, China, Europe, and Australia lead in global contributions to cognitive load and educational psychology research. However, there is a notable disparity between developed and developing countries, likely due to differences in academic infrastructure and research funding. Regional educational practices and cultural factors also play a role in shaping cognitive load and learning outcomes. For example, cognitive load may be distributed differently in cultures that emphasise collaborative learning than in individualistic cultures where self-study is prioritized. Bridging these gaps requires greater international collaboration and knowledge exchange, notably to support emerging research in low-resource settings.

Author and Country Contributions

Authors like K. McLaughlin, A. Dubrowski, and D.M. Irby are prominent contributors with high local impact based on metrics such as the h-index and m-index. These researchers have been instrumental in advancing cognitive load theory, especially concerning health sciences and instructional design. The United States remains the primary contributor to this field, with many studies originating from top academic institutions and benefiting from robust international collaborations. Countries like Canada and Australia also demonstrate high levels of international cooperation, while regions like Germany, Denmark, and Iran focus more on domestic research. This distribution highlights the need for diverse perspectives to strengthen global research in educational psychology.

Critical Articles and Emerging Topics

Several influential articles have shaped current understanding and practice in cognitive load theory:

- Makransky & Mayer (2021) highlighted the effectiveness of immersive virtual environments in managing cognitive load, emphasizing the practical applications of VR in education.

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- Chandler & Sweller (1992) remain foundational, demonstrating that reducing extraneous cognitive load through integrated instruction significantly improves learning outcomes. This study continues to be relevant as it aligns with current digital learning challenges.

Emerging topics in recent years include "executive function," "adaptive learning," and "e-learning," reflecting the integration of cognitive psychology with technological advancements. Terms like "mental health" and "motivation" are also increasingly prominent, indicating a holistic approach that considers emotional well-being alongside cognitive load in learning.

Factors Influencing Psychological and Cognitive Load

Innovative instructional media, such as videos, simulations, and adaptive learning technologies, effectively enhance learning outcomes by managing cognitive load. For example, well-designed simulations allow learners to practice complex tasks safely, reducing extraneous load and promoting germane load through active engagement. However, overuse or poor technology implementation can lead to cognitive overload, hindering learning effectiveness. Educators should adopt strategies that balance instructional media with cognitive capacity, incorporating breaks, simplified interfaces, and clear guidance to prevent overload.

Measuring Cognitive Load: Methods and Implications

Accurate measurement of cognitive load is essential for evaluating learning environments and designing targeted interventions. Physiological methods, like pupillometry, are particularly effective in high-stakes or real-time monitoring contexts, such as VR environments, due to their objective measurement of cognitive load. Meanwhile, psychometric methods, like the Paas scale and the Multidimensional Cognitive Load Scale for Physical and Online Lectures (MCLS-POL), offer practical solutions for various educational settings, providing insights into mental effort and overall cognitive load. These tools enable educators to adjust content and format to better align with students' cognitive capacities.

Emotional Factors in Cognitive Load Management

Emotions significantly influence cognitive load and motivation, particularly in online and hybrid learning settings. Negative emotions, such as anxiety and boredom, can increase cognitive load and reduce learning effectiveness, whereas positive emotions, like curiosity and enthusiasm, enhance engagement and motivation. Effective cognitive load management in digital environments involves instructional strategies and emotional support mechanisms, such as feedback systems and interactive activities, that foster a positive learning experience.

Emerging Research Areas and Interdisciplinary Potential

The impact of AI-driven educational technologies, such as adaptive learning platforms and intelligent tutoring systems, represents a promising direction for future research. These tools can personalize learning experiences by adjusting cognitive load based on individual performance, offering targeted interventions that enhance learning. Additionally, immersive environments, like VR, present opportunities to explore cognitive load in highly interactive contexts. Researchers might employ interdisciplinary methodologies, integrating insights from neuroscience and behavioural economics to understand cognitive load dynamics better and optimize educational technologies.

This section provides a comprehensive analysis of cognitive load research in educational psychology by linking observed trends and patterns with foundational theories and identifying specific drivers of research focus. Integrating instructional technology and attention to psychological factors offers actionable insights for educators and policymakers aiming to enhance learning effectiveness. Moving forward, interdisciplinary collaborations and regional diversity in research will be essential for addressing the complex challenges of cognitive load management in diverse educational contexts.

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Recommendation

Based on the findings of this study, the following recommendations are provided, categorized into distinct areas for clarity and practical application.

Educational Policy

Policymakers can leverage the insights from this research to design more inclusive and supportive frameworks that address psychological and cognitive load challenges across diverse educational contexts:

- Bridge the Research Gap: Encourage international collaboration to reduce disparities in research contributions between developed and developing countries. Establish funding and support programs to enhance research capacity in lower-resourced regions to promote equitable knowledge production.
- Develop Inclusive Policies: Create policies that support diverse learning environments, particularly for digital and hybrid learning. This includes funding initiatives for affordable access to digital tools and internet connectivity in underserved areas, helping to reduce barriers to effective technology adoption.
- Emphasize Emotional and Cognitive Well-being: Integrate guidelines prioritising cognitive and emotional support within educational policies. For instance, mental health support programs tailored for online learners can help manage anxiety and stress, improving cognitive load management and overall learning outcomes.

Instructional Design

Instructional designers and educators are critical in implementing strategies that minimize extraneous cognitive load while enhancing germane cognitive load. The following recommendations are offered to support effective instructional design: Minimize Extraneous Load. Design instructional materials that eliminate unnecessary complexity. This includes using clear, concise language, structured layouts, and simplified visual elements. Reducing extraneous load allows students to focus on core content, improving comprehension and retention. Enhance Germane Load Employ techniques that promote active engagement and schema construction, such as embedding quizzes, interactive exercises, and concept mapping. These activities encourage students to process information deeply, fostering long-term retention and practical application of knowledge. Leverage Innovative Technologies: Incorporate tools like simulations and interactive media in instructional design to create immersive learning experiences. For example, medical students can benefit from virtual simulations that mimic real-world scenarios, allowing them to practice skills in a controlled environment, enhancing germane cognitive load.

Technology Integration

Training and Support: Offer training sessions for students and educators to ensure effective technology adoption. For example, brief tutorials on learning management systems can enhance user confidence, especially for individuals unfamiliar with digital platforms. Address Emotional Well-being in Digital Learning: Recognize the role of emotions in technology acceptance and learning outcomes. Integrate gamification elements, such as progress rewards and interactive challenges, to increase engagement and reduce anxiety. Additionally, incorporating mindfulness activities into online courses can help students manage stress and maintain focus.

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Future Research Directions

To build a more comprehensive understanding of cognitive load and psychological factors in education, future research should consider the following directions: Explore Underrepresented Regions and Disciplines. Conduct research in diverse geographical and disciplinary contexts to enrich the knowledge base. This can help identify unique cognitive load challenges in various cultural or institutional settings and contribute to globally relevant educational practices. Conduct Longitudinal Studies. Examine the long-term effects of cognitive load and psychological factors on learning outcomes. Longitudinal studies could provide insights into how cognitive load management impacts knowledge retention and skill development over extended periods. Develop and Validate New Measurement Tools. Innovate and validate instruments capable of capturing cognitive load dynamics in increasingly complex and hybrid educational settings. For instance, tools that measure real-time cognitive load fluctuations in virtual environments would be valuable for understanding how learners respond to immersive educational experiences. Interdisciplinary Research Encourage research that bridges cognitive load theory with other fields, such as neuroscience or behavioural economics, to gain novel insights into learning processes. Neuroscientific studies on brain activity during learning tasks could reveal underlying mechanisms of cognitive load, while behavioural economics could inform strategies to optimize motivation and engagement in learning environments.

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