DEVELOPING KNOWLEDGE RECODING ABILITY THROUGH INFORMATION TECHNOLOGIES: A CONCEPTUAL AND METHODOLOGICAL FRAMEWORK

Niyozmetov Bahodir Abdullayevich
Master's student at Asia International University

Abstract. The contemporary learning environment requires students not only to acquire information but also to reorganize it into forms that support understanding, retrieval, transfer, and practical use. This article conceptualizes knowledge recoding ability as the deliberate transformation of content from one representational format into another while preserving semantic accuracy and improving cognitive accessibility. Examples include converting prose into a concept map, a diagram into an explanatory text, a dataset into a visual model, or a theoretical rule into an algorithm or simulation. Drawing on dual coding theory, cognitive load theory, generative learning, self-explanation, retrieval practice, and research on multiple representations, the study proposes a five-stage pedagogical model: diagnosis, decomposition, representational translation, reconstruction, and verification-transfer. The framework integrates semantic, representational, technological, and metacognitive components and specifies instructional conditions for its development through digital tools. An analytic assessment rubric is also offered to evaluate semantic fidelity, structural coherence, representational suitability, technological execution, and reflective justification. The article argues that information technologies improve learning only when they are used as cognitive instruments rather than as decorative delivery channels. The proposed model can guide curriculum design, digital task construction, and teacher education in higher education settings, while also providing a basis for subsequent empirical validation.
Keywords: knowledge recoding; information technologies; multiple representations; cognitive load; generative learning; digital pedagogy; higher education

1. Introduction

Digitalization has changed the conditions under which knowledge is produced, represented, accessed, and communicated. Learners encounter the same concept as written explanation, infographic, video, simulation, spreadsheet, code, diagram, or interactive model. Access to these formats does not automatically produce deep learning. The decisive issue is whether the learner can identify the invariant meaning of a concept, separate essential relations from surface features, and reconstruct the content in a new form without semantic distortion. This capacity is referred to in this article as knowledge recoding ability.

Knowledge recoding is more demanding than copying, summarizing, or formatting. It requires a learner to analyze the internal structure of information, select an appropriate representational system, transform the content, and justify the transformation. For example, converting a textbook paragraph into a concept map requires recognition of concepts and relations; converting a process diagram into an algorithm requires sequencing and conditional reasoning; and converting numerical data into a chart requires decisions about variables, scale, and visual emphasis. Each task combines subject knowledge with representational judgment and technological competence.

The educational importance of this ability is supported by several established lines of research. Dual coding theory explains the potential value of coordinating verbal and non-verbal representations (Paivio, 1986). Multimedia learning research shows that meaningful integration of words and visuals can improve comprehension when design respects the limits of working memory (Mayer, 2009). Cognitive load theory emphasizes that poorly designed representations may increase extraneous processing and obstruct learning (Sweller, 1988; Sweller, Ayres, & Kalyuga, 2011). Research on self-explanation, retrieval practice, and generative learning further indicates that learning becomes more durable when students actively reconstruct and explain knowledge rather than passively review it (Chi, de Leeuw, Chiu, & LaVancher, 1994; Roediger & Karpicke, 2006; Fiorella & Mayer, 2015).

Despite these converging findings, educational practice often treats information technology as a channel for presenting ready-made content. Students watch slides, receive digital handouts, or complete template-driven tasks without engaging in the deeper representational work required for knowledge transformation. Consequently, digital fluency may remain procedural while conceptual understanding remains fragile. The purpose of this article is to formulate a coherent pedagogical framework for developing knowledge recoding ability through information technologies. The objectives are to define the construct, identify its components, propose an instructional cycle, specify appropriate digital task types, and offer assessment criteria suitable for higher education and teacher education contexts.

2. Methodological Approach

This study is conceptual and methodological rather than experimental. It uses analytical synthesis, comparative interpretation, and pedagogical modeling to integrate findings from cognitive psychology, multimedia learning, instructional design, and digital education. The analysis focuses on established theories and research traditions that explain how learners process multiple representations, manage cognitive load, generate explanations, retrieve knowledge, and regulate learning.

The conceptual synthesis followed three steps. First, core mechanisms relevant to recoding were identified: semantic elaboration, representational translation, externalization, retrieval, and metacognitive monitoring. Second, these mechanisms were mapped onto typical information-technology-supported tasks, including concept mapping, data visualization, algorithm construction, multimedia explanation, and simulation. Third, the mechanisms and tasks were organized into a staged instructional model and an assessment rubric. Because the article does not report an empirical intervention, it makes no claims about effect sizes or causal impact. Its contribution is a theoretically grounded model that can be operationalized and tested in later experimental research.

3. Theoretical Foundations of Knowledge Recoding

3.1. Recoding as semantic transformation

At the cognitive level, recoding is a transformation of representation rather than a replacement of meaning. The learner must preserve the conceptual core while changing the external form. This process resembles deep processing because it requires attention to relations, categories, causal links, hierarchy, and conditions of application (Craik & Lockhart, 1972). A successful recoding therefore has two simultaneous properties: semantic fidelity and representational improvement. The new representation should remain accurate while making the content easier to understand, remember, compare, retrieve, or apply.

This distinction is important because visually attractive products can still be conceptually weak. A colorful infographic may omit causal relations; a concept map may contain disconnected labels; and a presentation may simplify a theory until its defining conditions disappear. Knowledge recoding must therefore be evaluated by the quality of meaning preserved and reorganized, not by surface aesthetics alone.

3.2. Multiple representations and dual coding

Multiple representations can support learning by distributing information across complementary forms. Ainsworth's (2006) DeFT framework explains that representations may complement one another, constrain interpretation, and support the construction of deeper understanding. Larkin and Simon (1987) similarly showed that diagrams can make relational information computationally efficient by placing relevant elements near one another and reducing search demands. These benefits are not automatic. Learners must understand the representational conventions and coordinate information across forms.

Dual coding theory proposes partially independent verbal and non-verbal systems, creating opportunities for richer encoding and retrieval when representations are meaningfully connected (Paivio, 1986). In pedagogical terms, recoding a verbal explanation into a diagram or reconstructing a diagram in words can create multiple retrieval routes. However, merely adding pictures to text does not constitute deep recoding. The learner must explain how elements correspond and why the selected representation is appropriate for the content.

3.3. Cognitive load and instructional guidance

Recoding tasks can reduce cognitive load by organizing complex information, but they can also overload learners when too many tools, formats, or design choices are introduced simultaneously. Cognitive load theory distinguishes between the inherent complexity of the content and avoidable processing caused by poor design (Sweller, 1988; van Merrienboer & Sweller, 2005). Novices may struggle to identify the structure of a topic and operate unfamiliar software at the same time. Therefore, early recoding tasks should use worked examples, partial templates, cueing questions, and explicit criteria.

As expertise develops, support should be gradually reduced. This balance is consistent with evidence that minimally guided instruction is often ineffective for novices dealing with complex material (Kirschner, Sweller, & Clark, 2006). The educational objective is not permanent dependence on templates, but a progression from guided transformation to independent representational decision-making.

3.4. Generative learning, self-explanation, and retrieval

Recoding is generative because it requires learners to select relevant information, organize it, and integrate it with prior knowledge. Fiorella and Mayer (2015) describe such activities as generative learning strategies. Self-explanation is especially relevant: when learners explain why a representation is valid, they expose gaps, repair misconceptions, and connect procedures with principles (Chi et al., 1994).

Retrieval practice adds another essential mechanism. A recoded product should not be created only while source material remains visible. After guided practice, students should reconstruct key knowledge from memory, compare their output with the source, and revise errors. Retrieval strengthens long-term retention and reveals whether the representation is genuinely understood rather than mechanically reproduced (Roediger & Karpicke, 2006; Karpicke & Blunt, 2011).

4. Structure of Knowledge Recoding Ability

Knowledge recoding ability is defined here as an integrated capacity to analyze knowledge, identify its structural relations, transform it into an alternative representation through suitable information technologies, and evaluate the accuracy and usefulness of the resulting representation. The construct includes four interdependent components.

Table 1. Components and observable indicators of knowledge recoding ability

Component	Core actions	Key indicators
Semantic component	Identifies key concepts, causal relations, conditions, exceptions, and hierarchy; distinguishes essential from secondary information.	Semantic accuracy; completeness; absence of conceptual distortion.
Representational component	Selects a form that matches the structure of the content; translates between text, diagram, table, formula, algorithm, model, and multimedia explanation.	Representational suitability; coherence; correspondence between forms.
Technological component	Uses digital tools to externalize, edit, compare, visualize, simulate, and share knowledge.	Functional tool use; technical clarity; accessibility; data integrity.
Metacognitive component	Plans the transformation, monitors information loss, checks the result, explains design choices, and revises the product.	Justification; error detection; revision quality; transfer to a new task.

The components operate as a coordinated system. Strong software skills cannot compensate for weak semantic understanding, and accurate subject knowledge does not guarantee an effective representation. The learner must connect meaning, form, tool, and self-regulation. This integrated view also prevents a narrow interpretation of digital competence as the ability to operate applications.

5. A Five-Stage Pedagogical Model

The proposed model organizes knowledge recoding as a recurrent five-stage cycle. Each stage has a distinct instructional function, but the stages are iterative rather than strictly linear. Verification may reveal the need to return to decomposition, and transfer to a new problem may require a different representation.

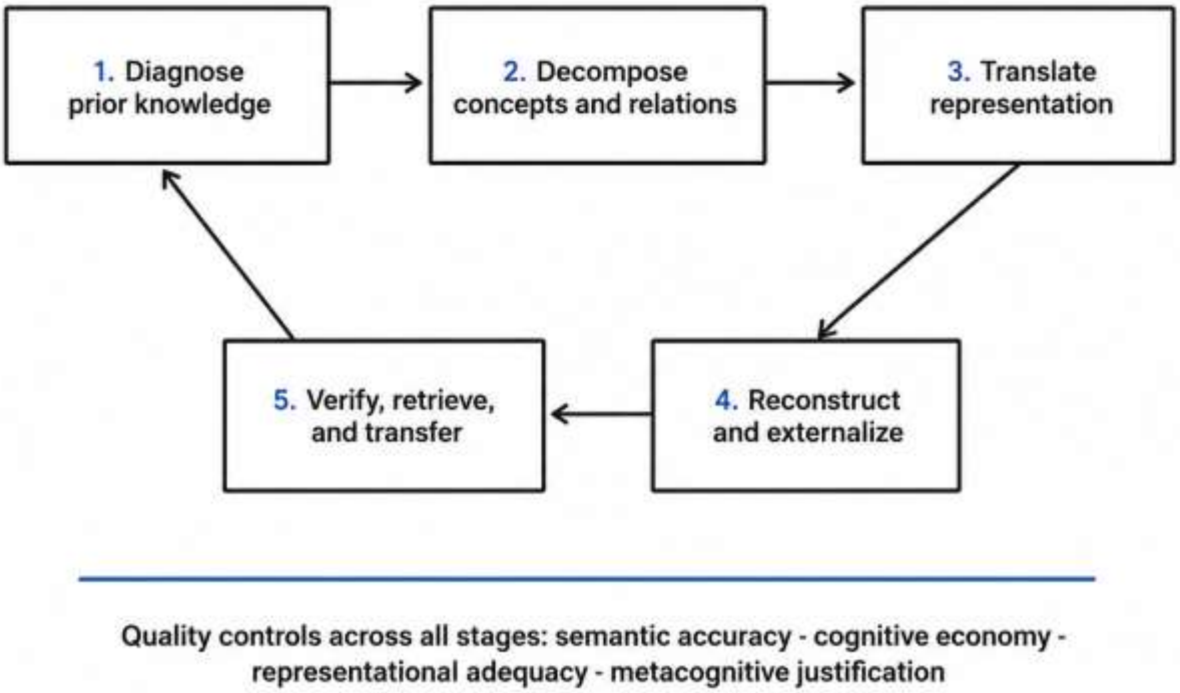

Figure 1. Five-stage cycle for developing knowledge recoding ability

Stage 1: Diagnosis of prior knowledge. The learner activates existing knowledge, identifies unfamiliar concepts, and determines the original structure of the material. Digital quizzes, annotation tools, and short retrieval prompts can reveal misconceptions and gaps. The instructor uses the diagnosis to calibrate task complexity and support.

Stage 2: Decomposition of concepts and relations. The learner separates definitions, examples, variables, causal links, procedures, and exceptions. Highlighting, tagging, digital note systems, and structured worksheets help make the internal architecture of the topic visible. The key question is not "What words appear?" but "How are the ideas related?"

Stage 3: Representational translation. The learner selects and applies a new representational system. A narrative may become a timeline, taxonomy, flowchart, concept map, table, formula, algorithm, or simulation. Tool choice must follow the epistemic structure of the content. A process is usually better represented as a sequence or flow, whereas classification is better represented as a hierarchy or matrix.

Stage 4: Reconstruction and externalization. The learner produces a coherent digital artifact and explains the logic of its construction. This stage includes editing, linking, labeling, adding evidence, and reducing redundancy. Peer comparison is useful because different representations make different assumptions visible.

Stage 5: Verification, retrieval, and transfer. The learner checks semantic fidelity against the source, reconstructs key parts from memory, and applies the representation to a new example or problem. Verification should detect omitted conditions, false causal links, scale errors, and misleading visual emphasis. Transfer confirms whether the representation supports flexible use rather than one-time reproduction.

6. Information-Technology-Supported Instructional Solutions

Information technologies contribute to knowledge recoding when they support cognitive operations that would otherwise be difficult, slow, or invisible. The following task architecture aligns digital tools with the structure of the learning objective.

Table 2. Instructional tasks for technology-supported knowledge recoding

Recoding task	Digital environment	Primary cognitive operation	Quality safeguard
Text to concept map	Concept-mapping software or diagram editor	Hierarchy, proposition, cross-link, conceptual compression	Students explain every link with a relation phrase.
Process description to flowchart or algorithm	Flowchart editor, presentation software, coding notebook	Sequence, condition, feedback, procedure	The output is tested with a new case.
Dataset to visual explanation	Spreadsheet, statistical or visualization software	Variable selection, comparison, trend, scale	Students justify chart type and identify possible distortion.
Diagram to written explanation	Annotation and word-processing tools	Verbalization, inference, causal explanation	The text must explain relations, not only name elements.
Theory to simulation or scenario	Simulation platform, interactive presentation, spreadsheet model	Parameterization, prediction, consequence	Assumptions and limits are stated explicitly.

Recoding task	Digital environment	Primary cognitive operation	Quality safeguard
Lecture content to retrieval artifact	Flashcard system, quiz tool, digital notebook	Cue design, recall, spacing, feedback	Questions require reconstruction, not recognition only.
Multiple sources to synthesis matrix	Spreadsheet, database, collaborative document	Comparison, source evaluation, integration	Claims are linked to evidence and conflicting findings are retained.

Several design principles are essential. First, technology should be selected after the representational need is identified. Tool-first instruction often produces decorative output rather than conceptual transformation. Second, students should compare at least two possible representations and explain which one better fits the content. Third, the original and recoded forms should be displayed side by side during guided practice so that correspondence can be examined. Fourth, tasks should gradually shift from transformation with visible source material to reconstruction from memory. Fifth, accessibility should be treated as part of representational quality: labels, contrast, readable structure, captions, and alternative text influence whether the artifact communicates meaning effectively.

Artificial-intelligence-supported tools can assist brainstorming, summarization, and format conversion, but they introduce a verification problem. Generated content may omit conditions, invent relations, or produce fluent but inaccurate simplifications. Therefore, AI-assisted recoding should require source-based checking, explanation of edits, and clear separation between machine suggestions and the learner's validated final representation. The pedagogical value lies in critical comparison and revision, not in accepting automated output as authoritative.

7. Instructional Conditions for Effective Development

Progressive complexity. Tasks should begin with short, well-structured content and familiar tools, then advance to ill-structured problems, competing representations, and independent tool selection.

Explicit modeling. Instructors should demonstrate how they identify concepts, choose a representation, detect information loss, and revise the result. Think-aloud modeling makes expert decisions observable.

Representational comparison. Students should analyze alternative versions of the same knowledge and discuss what each representation reveals, hides, simplifies, or distorts.

Feedback on meaning before aesthetics. Evaluation should prioritize conceptual accuracy and structural coherence. Visual design becomes relevant after the knowledge structure is correct.

Retrieval and transfer. Students should reproduce and adapt representations without continuous access to the original source, then use them to solve a new problem.

Reflective justification. Every final artifact should include a short explanation of why the format and tool were chosen, what was omitted, and how accuracy was checked.

Ethical and accessible use. Students should cite sources, protect data, acknowledge AI assistance where required, and design artifacts that remain readable and usable for diverse audiences.

8. Assessment Framework

Assessment should measure the quality of the transformation process and the resulting representation. Product-only grading can reward polished appearance while overlooking conceptual error. A combined approach includes artifact analysis, oral or written justification, a brief reconstruction task, and transfer to a new context.

Table 3. Analytic rubric for assessing knowledge recoding products

Criterion	1 - Initial	2 - Developing	3 - Proficient	4 - Advanced
Semantic fidelity	Major misconceptions; essential relations missing.	Partly accurate; several omissions or ambiguous relations.	Accurate core meaning with minor omissions.	Complete and precise; conditions, exceptions, and relations preserved.
Structural coherence	Elements are disconnected or incorrectly ordered.	Basic structure is visible but inconsistent.	Logical hierarchy or sequence is clear.	Structure is optimized for comprehension and comparison.
Representational suitability	Chosen format conflicts with content structure.	Format is usable but only partly appropriate.	Format matches the main learning purpose.	Format is deliberately selected and alternatives are critically compared.

Criterion	1 - Initial	2 - Developing	3 - Proficient	4 - Advanced
Technological execution	Technical errors obstruct meaning.	Artifact functions but contains readability or data problems.	Tool is used accurately and accessibly.	Technology adds analytical value, interactivity, or efficient comparison.
Metacognitive justification	No explanation or verification.	Limited explanation; checking is superficial.	Choices are explained and accuracy is checked.	Limitations, information loss, revisions, and transfer are critically justified.

For research purposes, rubric scores can be supplemented with pre- and post-tests of conceptual understanding, delayed retrieval, transfer tasks, cognitive-load ratings, and analysis of revision logs. Reliability should be established through rater training and inter-rater agreement. Validity evidence should examine whether rubric performance predicts independent understanding and transfer rather than merely digital production skill.

9. Discussion

The proposed framework positions information technology as a cognitive instrument for reorganizing knowledge. Its central assumption is that learning improves when students actively transform representations while preserving meaning. This assumption connects research traditions that are often treated separately: multimedia learning explains the coordination of words and visuals; cognitive load theory explains design limits; generative learning explains active organization and integration; retrieval practice explains durable access; and metacognitive regulation explains planning, monitoring, and revision.

The framework also clarifies why some digital assignments have limited educational value. When students are asked to make a presentation without criteria for semantic structure, they may copy text into slides. When they create a concept map without relation labels, they may produce a cluster of terms rather than a model of knowledge. When they generate a chart without examining scale and variable selection, they may create a persuasive but misleading visual. In each case, the missing element is not technology but disciplined recoding.

Several risks require attention. First, complex software may consume working-memory resources that should be devoted to understanding; this is especially problematic for novices. Second, representational simplification can remove uncertainty, exceptions, or contextual conditions. Third, unequal access to devices and digital experience may confound assessment of conceptual ability. Fourth, automated tools can create plausible but inaccurate transformations. These risks support a guided, criterion-based, and ethically transparent approach rather than unrestricted technology use.

The framework is especially relevant to teacher education. Future teachers need to interpret curriculum content, redesign explanations for different learners, produce visual and interactive materials, and evaluate whether representations preserve disciplinary meaning. Training them to recode knowledge systematically can strengthen both subject understanding and pedagogical content knowledge. It can also improve their ability to design accessible resources, diagnose misconceptions, and adapt explanations across classroom situations.

10. Practical Implications for Higher Education

At the course level, one recoding task can be integrated into each major topic. Students may convert a theoretical reading into a concept map, convert the map into an oral explanation, and later reconstruct the theory through a transfer problem. This sequence turns representation into a recurring learning practice rather than an isolated digital assignment.

At the curriculum level, departments can define a progression of representational competencies. Early courses may emphasize accurate transformation with templates; intermediate courses may require comparison of formats; advanced courses may require independent selection, simulation, and critical evaluation of information loss. Shared rubrics can make expectations consistent across subjects.

At the institutional level, professional development should focus on task design rather than software demonstrations alone. Instructors need examples of how digital tools support specific cognitive operations, how to scaffold novices, and how to evaluate semantic quality. Learning-management systems can support portfolios in which students retain successive versions, feedback, reflections, and evidence of transfer.

11. Limitations and Directions for Future Research

The article presents a conceptual framework and therefore requires empirical validation. The proposed components and stages should be tested across disciplines, educational levels, and digital environments. Experimental studies can compare guided recoding with conventional note-taking or presentation tasks, while longitudinal studies can examine whether the ability transfers across courses.

Future research should also investigate the relative difficulty of different representational transformations. Text-to-diagram, diagram-to-text, data-to-visualization, and theory-to-simulation tasks may rely on partly distinct skills. Additional work is needed to determine how prior knowledge, spatial ability, digital fluency, and metacognitive skill interact with recoding performance. Finally, research should examine how AI-supported transformations affect learning when students are required to verify, revise, and justify machine-generated representations.

12. Conclusion

Knowledge recoding ability is a critical but under-specified outcome of digital education. It involves more than presenting information in a new format. The learner must analyze meaning, select a suitable representational system, use technology to externalize the transformation, and verify that the new form remains accurate and useful. The five-stage model proposed in this article - diagnosis, decomposition, translation, reconstruction, and verification-transfer - provides a structured route for developing this ability.

Information technologies are most educationally valuable when they make cognitive work visible and revisable. Concept maps, diagrams, spreadsheets, simulations, coding environments, multimedia tools, and AI-supported systems can all contribute, but only when tasks prioritize semantic fidelity, representational appropriateness, retrieval, and reflection. The framework offers a basis for curriculum design, instructional practice, assessment, and future empirical research on the formation of knowledge recoding ability in higher education.

References

Ainsworth, S. (2006). DeFT: A conceptual framework for considering learning with multiple representations. Learning and Instruction, 16(3), 183-198. https://doi.org/10.1016/j.learninstruc.2006.03.001

Baddeley, A. (2000). The episodic buffer: A new component of working memory? Trends in Cognitive Sciences, 4(11), 417-423. https://doi.org/10.1016/S1364-6613(00)01538-2

Chi, M. T. H., de Leeuw, N., Chiu, M.-H., & LaVancher, C. (1994). Eliciting self-explanations improves understanding. Cognitive Science, 18(3), 439-477. https://doi.org/10.1207/s15516709cog1803_3

Craik, F. I. M., & Lockhart, R. S. (1972). Levels of processing: A framework for memory research. Journal of Verbal Learning and Verbal Behavior, 11(6), 671-684. https://doi.org/10.1016/S0022-5371(72)80001-X

Dunlosky, J., Rawson, K. A., Marsh, E. J., Nathan, M. J., & Willingham, D. T. (2013). Improving students' learning with effective learning techniques: Promising directions from cognitive and educational psychology. Psychological Science in the Public Interest, 14(1), 4-58. https://doi.org/10.1177/1529100612453266

Fiorella, L., & Mayer, R. E. (2015). Learning as a generative activity: Eight learning strategies that promote understanding. Cambridge University Press.

Kalyuga, S. (2009). Managing cognitive load in adaptive multimedia learning. Information Science Reference.

Karpicke, J. D., & Blunt, J. R. (2011). Retrieval practice produces more learning than elaborative studying with concept mapping. Science, 331(6018), 772-775. https://doi.org/10.1126/science.1199327

Kirschner, P. A., Sweller, J., & Clark, R. E. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching. Educational Psychologist, 41(2), 75-86. https://doi.org/10.1207/s15326985ep4102_1

Larkin, J. H., & Simon, H. A. (1987). Why a diagram is (sometimes) worth ten thousand words. Cognitive Science, 11(1), 65-100. https://doi.org/10.1111/j.1551-6708.1987.tb00863.x

Mayer, R. E. (2009). Multimedia learning (2nd ed.). Cambridge University Press.

Moreno, R., & Mayer, R. (2007). Interactive multimodal learning environments. Educational Psychology Review, 19, 309-326. https://doi.org/10.1007/s10648-007-9047-2

Paivio, A. (1986). Mental representations: A dual coding approach. Oxford University Press.

Roediger, H. L., III, & Karpicke, J. D. (2006). Test-enhanced learning: Taking memory tests improves long-term retention. Psychological Science, 17(3), 249-255. https://doi.org/10.1111/j.1467-9280.2006.01693.x

Spiro, R. J., Feltovich, P. J., Jacobson, M. J., & Coulson, R. L. (1991). Cognitive flexibility, constructivism, and hypertext: Random access instruction for advanced knowledge acquisition in ill-structured domains. Educational Technology, 31(5), 24-33.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. Cognitive Science, 12(2), 257-285. https://doi.org/10.1207/s15516709cog1202_4

Sweller, J., Ayres, P., & Kalyuga, S. (2011). Cognitive load theory. Springer.

UNESCO. (2023). Global education monitoring report 2023: Technology in education - A tool on whose terms? UNESCO.

van Merrienboer, J. J. G., & Sweller, J. (2005). Cognitive load theory and complex learning: Recent developments and future directions. Educational Psychology Review, 17, 147-177. https://doi.org/10.1007/s10648-005-3951-0

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. Theory Into Practice, 41(2), 64-70. https://doi.org/10.1207/s15430421tip4102_2