American Journal of Advanced Multidisciplinary Innovation and Research (AJAMIR)

E-ISSN: XXXX-XXXX ● Website: www.ajamir.com ● Email: editor@ajamir.com

Digital Note-Taking Strategies and Deep Comprehension

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Abstract

Digital note-taking has become a routine component of contemporary learning because laptops, tablets, digital pens, cloud notebooks, searchable databases, lecture recordings, and artificial-intelligence-supported study tools allow learners to capture and reorganize information with unprecedented speed. Greater capture efficiency, however, does not automatically produce deeper comprehension. A 2024 meta-analysis of 24 studies reported that typed lecture notes generally contained substantially more material, while students taking and reviewing handwritten notes demonstrated a small but statistically significant achievement advantage. At the same time, earlier replication research cautions against interpreting note-taking medium as a simple causal determinant of learning, because differences between longhand and digital conditions have not been consistently reproduced across experiments.

This paper develops a Generative Digital Note-Taking Framework for Deep Comprehension that shifts attention from the device used to the cognitive operations performed while taking and reviewing notes. The framework distinguishes four strategies: verbatim digital transcription, structured digital note-taking, concept-linked digital note-making, and generative note-taking combined with retrieval-oriented review. Its central premise is that digital notes contribute most strongly to deep comprehension when learners select rather than indiscriminately capture information, reorganize ideas into meaningful structures, explain relationships in their own language, generate questions, connect concepts with prior knowledge, and later retrieve information without simply rereading it. Recent evidence supports this strategy-centered interpretation. A 2026 experiment found that explicit instruction in deep note-taking improved mathematics understanding independently of the physical note-taking medium, while a randomized study of 134 teacher candidates found limited overall differences among note-taking formats but stronger delayed retention for the Cornell method than for conventional sentence notes.

The study employs a conceptual-methodological design accompanied by transparent simulated analysis. Four digital strategies are compared across immediate comprehension and retention after 48 hours, one week, and two weeks. A 2020 randomized experiment involving 405 secondary-school students found that note-taking alone and note-taking combined with an LLM produced better comprehension and retention than LLM use alone, whereas 2026 research on AI-supported note-taking suggests that carefully designed learner–AI interaction can outperform AI-only note generation.

Keywords: digital note-taking, deep comprehension, generative learning, Cornell notes, retrieval practice, digital learning, cognitive processing, note organization, AI-assisted note-taking, higher education

1. Introduction

Note-taking serves at least two educational functions. During learning, it can operate as an encoding process in which students attend to, interpret, select, and reorganize incoming information. After learning, the resulting notes become an external storage system that can support review, retrieval, comparison, and further knowledge construction. Research comparing digital and handwritten formats demonstrates that these two functions can interact differently with the chosen medium. Luo and colleagues found that laptop users recorded more words, idea units, and verbatim lecture strings than longhand note-takers, whereas longhand participants recorded more visual signals and images; subsequent achievement differences depended partly on whether notes were later reviewed and on the type of information being learned.

The popularity of digital note-taking creates clear practical advantages. Digital notes can be edited, searched, reorganized, duplicated, synchronized across devices, connected to multimedia resources, and revised over time. Recent higher-education design research demonstrates that purpose-built digital note-taking environments can support progressive reflection and conceptual development when their interface is aligned with the actual stages of learning rather than simply providing an empty electronic page. McKenzie and colleagues reported use of a staged web-based note-taking application with 189 initial-teacher-education students, finding that the system supported purposeful note-making decisions, progressive review, and reduced unnecessary cognitive burden within the designed seminar process.

Efficiency nevertheless creates a potential cognitive problem. Typing allows students to reproduce large quantities of lecture language rapidly, which can encourage verbatim capture rather than semantic transformation. Mueller and Oppenheimer's influential 2014 experiments initially associated laptop note-taking with poorer conceptual performance and greater verbatim transcription, although later direct replications found smaller and inconsistent modality differences. Morehead, Dunlosky, and Rawson's replication concluded that it was premature to declare one medium categorically superior because their experimental comparisons produced no consistent performance differences and only small nonsignificant meta-analytic effects favoring longhand within those direct replications.

The broader evidence now suggests a more nuanced position. Flanigan and colleagues' 2024 meta-analysis found that handwritten lecture notes were associated with a modest achievement advantage while typed notes substantially increased note volume. Yet recent experimental research increasingly indicates that how learners process information may be more important than the writing surface alone. Liu and Uesaka's 2026 experiment with 94 high-school students found a significant benefit of deep note-taking instruction for mathematics understanding while the tested note-taking medium itself did not produce a significant main effect. Their findings imply that teaching students to use notes cognitively and metacognitively may offer a more durable educational intervention than simply instructing them to abandon digital devices.

Artificial intelligence adds a further dimension to this problem. Digital platforms can now automatically transcribe lectures, summarize documents, extract key points, generate flashcards, and answer questions from uploaded readings. These tools can reduce routine workload, but they can also remove precisely the selection, compression, organization, and reconstruction processes through which note-taking may contribute to learning. A randomized 2025 study found that students who took notes, either independently or while also using an LLM, demonstrated better delayed comprehension and retention than students relying on an LLM alone. Emerging 2026 work similarly suggests that learner–AI collaborative note-taking can be more educationally effective than passive AI-only note generation when students remain cognitively involved.

2. Objectives of the Study

2.1 To Differentiate Digital Transcription from Generative Digital Note-Making

The first objective is to establish a conceptual distinction between digitally recording information and cognitively transforming information.

Verbatim transcription prioritizes completeness and speed. Generative note-making requires students to identify central claims, reorganize information, summarize ideas in their own words, relate new material to existing knowledge, and make meaningful decisions about what should and should not enter the note system.

The distinction is supported by research showing that typed notes tend to contain greater quantities of lecture information, while strategy-centered approaches such as Cornell note-taking explicitly require learners to select ideas, generate cues or questions, summarize, reflect, and review.

2.2 To Develop a Digital Strategy for Deep and Durable Comprehension

The second objective is to design a digital note-taking workflow that supports both initial understanding and delayed retention.The framework integrates structured note architecture, conceptual linking, question generation, self-explanation, retrieval-based review, and spaced revision. Recent experimental work suggests that structured approaches can improve aspects of delayed learning even when simple format comparisons produce relatively small differences. Yıldırım's randomized study found that the Cornell group outperformed conventional sentence-note users on the delayed retention assessment, while motivation was a particularly consistent predictor of retention across conditions.

2.3 To Position AI as a Note-Taking Scaffold Rather Than a Replacement for Cognitive Processing

The third objective is to develop principles for responsible AI-assisted note-taking.
AI can help learners reorganize notes, identify omissions, generate practice questions, clarify terminology, or compare competing explanations. It should not automatically replace the learner's first-pass selection and interpretation of important information.

Experimental evidence published in 2020 indicates that learners who engaged in note-taking retained more than those using an LLM alone, while current 2020 research suggests that learner–AI co-note-taking can be beneficial when AI support remains embedded within an active learner-controlled process.

3. Review of Literature

3.1 Note-Taking Medium, Encoding, and the Handwriting–Typing Debate

Mueller and Oppenheimer's 2014 study became highly influential by proposing that longhand note-taking can promote conceptual learning because slower handwriting encourages students to process and summarize rather than transcribe lectures verbatim. Their experiments reported greater verbatim overlap in laptop notes and weaker conceptual performance among laptop users in some conditions.

Subsequent replication work complicated this conclusion. Morehead, Dunlosky, and Rawson reproduced the general experimental structure while adding electronic writers and no-note conditions. Their findings showed some trends in favor of longhand but no consistent performance differences among groups; their combined direct-replication analysis produced only small nonsignificant longhand advantages. The authors therefore cautioned against treating the original finding as sufficient evidence for a simple medium hierarchy.

Luo and colleagues further demonstrated that digital and longhand note-taking produce different note characteristics rather than one medium being uniformly superior. Laptop users generated more textual material and verbatim strings, while longhand users incorporated more visual information. Learning outcomes depended partly on whether notes were reviewed, demonstrating that the product function of notes after the lecture can change the relationship between medium and achievement.

The more recent synthesis is somewhat more favorable to handwriting but remains compatible with a strategy-centered interpretation. Flanigan and colleagues' 2024 meta-analysis aggregated 24 studies from 21 articles and found a small achievement advantage for handwritten notes, with Hedges' $g=0.248$, while typed notes produced a much larger advantage in note volume, $g=0.919$. The findings demonstrate a genuine trade-off between information quantity and average academic achievement rather than proving that digital notes are inherently ineffective.

The most useful implication is therefore not that digital note-taking should be prohibited. Rather, digital systems need mechanisms that counteract the tendency toward excessive transcription and convert the speed, searchability, and reorganizability of digital media into opportunities for deeper cognitive engagement.

3.2 Structured, Generative, and Concept-Linked Note-Taking

Structured note-taking methods attempt to make the learner perform specific cognitive operations rather than leave strategy entirely to individual habit. The Cornell system divides notes into content, cue or question, and summary functions and later incorporates recitation, reflection, and review. Recent research explains its educational value through selective attention, organization, question generation, summary production, and elaborative rehearsal rather than through the visual page format itself.

Seo's recent investigation of Cornell strategy instruction emphasized precisely these processes: learners identify important information, organize ideas, formulate questions, summarize central meaning, and engage in later review. The study reported stronger comprehension outcomes for Cornell-trained learners and argued that explicit sustained strategy instruction is more useful than simply providing students with a note template without guidance.

Yıldırım's randomized controlled research offers a useful qualification. Among 134 teacher candidates assigned to Cornell, Parallel, Digital, or Sentence conditions, immediate post-test differences were limited, and only the Cornell–Sentence comparison was significant at delayed retention. Digital note-taking also produced lower reported cognitive load than some other strategies. These findings caution against assuming large learning differences among every structured method while supporting the broader claim that delayed retention may depend upon the processing and review routines built into a strategy.

The importance of strategy has been strengthened further by Liu and Uesaka's 2026 experimental study. Their deep-note-taking instruction activated cognitive, metacognitive, and resource-management functions and improved mathematics knowledge post-tests. By contrast, changing whether students wrote in textbooks or separate notebooks did not itself create a significant performance effect. The result supports an interpretation in which note-taking quality is determined substantially by the learner's cognitive approach.

Digital environments may be especially suitable for concept linking because they permit learners to reorganize notes after initial capture, create hyperlinks, attach diagrams, tag concepts, combine information from lectures and readings, and maintain evolving summaries. The pedagogical value of such affordances depends on whether students use them to reconstruct knowledge rather than merely accumulate content.

3.3 Digital Distraction, AI Assistance, and Cognitive Offloading

Digital note-taking occurs within environments that can also contain messaging, browser tabs, social media, entertainment, notifications, and unrelated applications. The 2024 meta-analysis literature includes extensive research on digital distraction, and Flanigan and Titsworth's work specifically examines how off-task digital behavior can interfere with lecture note-taking and learning. The educational consequences of device use therefore depend partly on attentional regulation as well as on typing itself.

The emergence of large language models changes cognitive offloading from a distraction problem into a learning-design problem. An AI tool can provide an apparently high-quality summary without requiring the learner to decide which information is central or how concepts relate. Kreijkes and colleagues' preregistered randomized experiment involved 405 students aged 14–15 who studied texts using note-taking, an LLM, or combinations of both. Note-taking alone and note-taking plus LLM use produced significant benefits for comprehension and retention relative to LLM-only use after three days, even though students generally preferred the LLM and perceived it as helpful.

This distinction between perceived ease and durable learning is important. A tool can reduce cognitive burden and make material easier to access while simultaneously removing desirable cognitive work. The educational solution is not necessarily to eliminate AI but to decide which processing should remain the learner's responsibility.

Current 2020 research on AI-powered note-taking points toward a hybrid model. Pi and colleagues compared learner–AI, AI-only, and learner-only note-taking in video-based STEM learning and reported benefits for learner–AI collaboration in knowledge acquisition, creativity, note quality, attention, and information integration. The emerging implication is that AI can be useful when it participates in an interactive note-making process rather than replacing the learner with an automatically generated record.

4. Research Methodology

4.1 Research Design

The study adopts a conceptual-methodological design supported by simulation-based comparative analysis.

No human participants were recruited, no actual student notes were collected, and no institutional achievement data were analyzed. The framework is derived from contemporary experimental, replication, meta-analytic, and design research on note-taking modality, structured note-taking, deep note-making, digital tools, and AI-assisted learning.

The numerical analysis is explicitly illustrative and is intended to demonstrate how a future empirical investigation could compare digital note-taking strategies over delayed comprehension intervals.

4.2 Generative Digital Note-Taking Framework

The proposed framework organizes digital note-making into seven functional stages.

Table 1: Generative Digital Note-Taking Framework for Deep Comprehension

Stage	Learner Action	Digital Affordance	Intended Cognitive Function
Select	Record only conceptually relevant information	Highlighting, concise text entry, stylus annotation	Directs attention toward important material
Compress	Rewrite ideas in shorter personal language	Editable summary blocks	Requires semantic transformation
Organize	Arrange ideas hierarchically or structurally	Headings, indentation, Cornell layout, tables	Makes conceptual structure visible
Connect	Relate current information to other concepts	Hyperlinks, tags, concept links, diagrams	Supports integration with prior and parallel knowledge
Question	Convert important content into questions	Cue fields, flashcard generation, collapsible prompts	Creates retrieval opportunities
Explain	Add brief self-explanations or examples	Annotation, comment fields, voice notes	Makes reasoning explicit
Retrieve and Revise	Reconstruct content before rereading and update notes later	Hidden-answer prompts, spaced reminders, versioning	Strengthens durable retention and error correction

The framework treats digital notes as an evolving knowledge representation rather than a transcript.

5. Analysis

5.1 Simulated Deep-Comprehension Retention

Table 2: Simulated Deep-Comprehension Scores Across Digital Note-Taking Strategies

Digital Note-Taking Strategy	Immediate	48 Hours	1 Week	2 Weeks	Two-Week Retention Relative to Initial Score
Verbatim Digital Transcription	70	60	49	41	58.6%
Structured Digital Notes	78	72	65	58	74.4%
Concept-Linked Digital Notes	83	78	72	66	79.5%
Generative Notes + Retrieval Review	86	83	79	75	87.2%

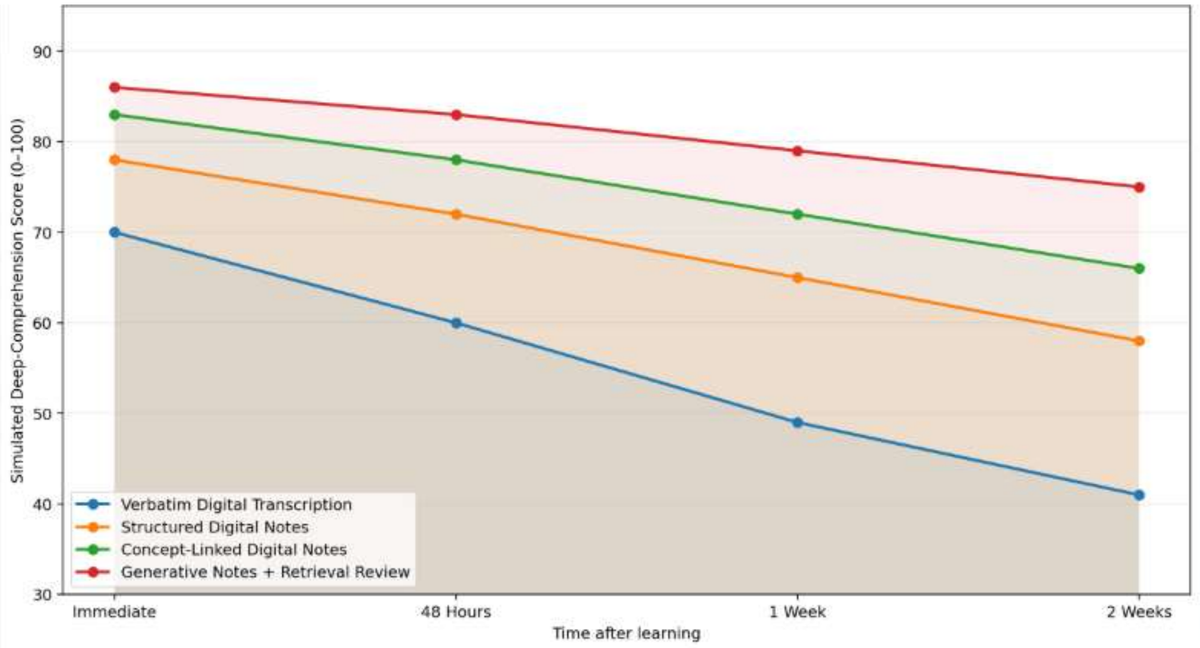
Note: All values are author-generated simulations and do not represent empirical student scores.
The simulation assumes that verbatim digital transcription can produce reasonable immediate performance because the learner retains substantial recent exposure and possesses a detailed external record. Its principal weakness becomes visible over time. Without conceptual restructuring or active retrieval, the simulated comprehension score declines from 70 to 41 over two weeks.

Structured notes preserve more information because major ideas, subideas, questions, and summaries are organized in a retrievable form. This pattern is broadly compatible with contemporary evidence showing that structured note methods can support delayed retention even when immediate performance differences are small.

Concept-linked notes perform more strongly because the learner is required to encode relationships among concepts rather than preserve isolated statements.The strongest simulated performance occurs when generative note-making is paired with retrieval. This strategy converts the notes into a study system rather than a static archive.

5.2 Area-Chart Analysis of Retention

Graph 1: Simulated Deep-Comprehension Retention Across Digital Note-Taking Strategies



The area chart emphasizes that the educational value of notes should be judged over time rather than only immediately after a lecture. All four simulated conditions experience some forgetting, but the slope differs substantially.

The largest decline occurs in verbatim transcription, where the note-taking process has captured information without requiring substantial reconstruction.Structured notes flatten the decline, while concept-linked notes preserve a still larger proportion of the initial score.

The smallest simulated decline occurs under generative notes combined with retrieval review. This illustrates the conceptual principle that a good note is not merely easy to reread; it can also be designed to withhold information temporarily so that the learner must retrieve it.

The graph does not claim that these exact trajectories occur in real students. Future empirical studies would require randomized assignment, validated comprehension measures, standardized instructional content, delayed testing, and controls for prior knowledge, motivation, typing skill, device preference, and review time.

5.3 Proposed Digital Deep-Comprehension Workflow

The analysis supports a three-phase workflow.

The first phase occurs during learning. Students should capture fewer complete sentences and instead identify claims, principles, mechanisms, examples, and uncertainties. Where lecture pace is high, temporary shorthand can be used, but the goal should remain semantic capture rather than transcription completeness.

The second phase occurs shortly after learning. Students reorganize the notes, remove duplication, complete incomplete relationships, generate a brief summary, identify two or three

unresolved questions, and connect the topic with earlier material. Purpose-built digital tools can support this progressive revision particularly well because notes remain editable and reorganizable over time.
The third phase converts the notes into a retrieval system. Headings or questions remain visible while explanations are hidden. Students attempt to reconstruct the idea, example, or causal relationship before checking their notes.

AI can be introduced most productively during the second and third phases. It can compare a learner's summary against the source, suggest missing relationships, generate alternative questions, challenge explanations, or identify ambiguities. The learner should remain responsible for deciding whether AI suggestions are accurate and for producing the first meaningful representation of the topic. This interpretation is consistent with emerging evidence that learner–AI collaborative note-taking can outperform AI-only automation.

6. Discussion

6.1 The Quality of Cognitive Processing Matters More Than Note Quantity

The first major implication is that completeness should not be treated as the primary measure of note quality. Digital devices are highly effective for capturing words, but learning does not necessarily increase in proportion to the quantity recorded. The 2024 meta-analysis demonstrates this contrast clearly: typed notes contained substantially more material, yet handwritten note-taking was associated with a modest average achievement advantage.

The likely educational issue is that transcription and comprehension place different demands on the learner. Transcription asks, *What did the lecturer say?* Deep note-making asks, What is the central idea, how is it related to the previous idea, why is it true, and what would count as an example or contradiction?

Digital tools can support either behavior. A laptop is therefore not intrinsically shallow, just as a handwritten notebook is not intrinsically deep. A learner can copy mechanically by hand and can engage in highly generative processing on a tablet or laptop.

The 2019 replication literature and 2026 deep-note-taking experiment reinforce this conclusion. Modality differences are not sufficiently consistent to justify reducing note-taking pedagogy to device prohibition, whereas explicit strategy instruction can alter learning processes more directly. Educators should consequently assess notes according to cognitive function: selection, structure, integration, explanation, and later retrieval.

6.2 Digital Tools Are Most Educationally Valuable When They Support Revision and Knowledge Connection

The second implication concerns what digital technology can do better than static paper without weakening cognitive engagement.

Digital notes are particularly useful for revision. A student can return to an earlier topic, reorganize its structure, link it to new material, update an explanation, add a visual representation, or attach an example from another source. McKenzie's staged application research illustrates how digital note environments can deliberately support progressive refinement rather than simple recording.

This capability is especially valuable for cumulative courses. A student learning statistics can connect confidence intervals to sampling distributions, hypothesis testing, and regression assumptions. A physics learner can link force models with energy models. A biology student can progressively connect molecular mechanisms to cellular and organism-level consequences.

Such links change notes from chronological lecture records into knowledge networks.The same principle applies to review. Students should not merely reopen the same page and reread highlighted sections. Digital note systems can convert headings into questions, hide explanations, create spaced reminders, and surface earlier notes when related concepts appear.This approach combines digital convenience with desirable cognitive effort.

6.3 AI Should Reduce Administrative Friction Without Eliminating Intellectual Friction

The third implication concerns artificial intelligence. AI can remove low-value work, but educators should distinguish low-value friction from productive intellectual friction.

Automatically fixing formatting, converting handwritten notes into searchable text, generating organizational labels, or identifying duplicate content may save time without undermining learning. Automatically producing the entire summary before the student has interpreted the material is more problematic because summarization itself can be part of the learning process.

The randomized 2020 LLM study provides an important warning: students preferred the LLM and often perceived it as more helpful, yet note-taking produced stronger comprehension and retention than LLM-only learning. Ease and perceived helpfulness should therefore not be treated as substitutes for durable learning outcomes.

At the same time, an entirely anti-AI position would ignore emerging evidence. Pi and colleagues' 2020 work indicates that learner–AI note-taking can improve outcomes relative to AI-only and learner-only conditions in video-based STEM learning when learners remain actively involved in organizing and integrating information.

The design principle should therefore be AI after or alongside learner cognition, not AI instead of learner cognition.

A student might first produce a three-sentence explanation of a difficult concept, then ask an AI system to challenge that explanation. The student can evaluate the critique and revise the note. The resulting activity retains intellectual ownership while using AI as a source of feedback.

7. Conclusion

Digital note-taking has transformed the mechanics of academic learning, but its educational effectiveness cannot be understood simply by comparing keyboards with pens. Digital systems can encourage rapid transcription and distraction, yet they can also provide powerful facilities for organization, revision, conceptual linking, search, multimedia integration, retrieval scheduling, and reflective improvement. The central issue is therefore not whether students use digital notes but how those digital notes are cognitively constructed.

The evidence reviewed in this paper supports a balanced interpretation. The 2024 meta-analysis shows a small average achievement advantage for handwritten lecture notes alongside a large typed-note advantage in information volume, while direct replication studies demonstrate that modality differences are not universally consistent. This combination cautions against both technological determinism and simplistic anti-device conclusions. Digital note-taking becomes educationally weak primarily when speed encourages unselective transcription or when the surrounding device environment fragments attention.

The more promising direction is strategy instruction. Structured formats such as Cornell notes encourage students to identify key ideas, formulate questions, summarize, reflect, and review. Recent randomized research shows some delayed-retention advantage for structured Cornell note-taking, and 2020 experimental evidence indicates that direct instruction in deep note-taking can improve understanding independently of the tested physical note medium. These findings suggest that universities should teach note-taking as an academic learning capability rather than assume that students have already learned how to do it effectively.

The proposed Generative Digital Note-Taking Framework therefore prioritizes selection, compression, organization, conceptual connection, questioning, self-explanation, and retrieval-based revision. The simulated analysis illustrates why these processes may become increasingly important as the time between exposure and assessment grows. Verbatim digital transcription produces the steepest hypothetical forgetting curve, while generative notes combined with retrieval show the strongest sustained simulated comprehension. These numerical patterns require empirical validation, but they offer a practical model for future controlled studies.

Artificial intelligence strengthens the need for this distinction. Automated transcription and summarization can produce excellent external records while reducing the cognitive work traditionally embedded in note-making. Yet AI can also become a productive partner when students remain responsible for interpreting, questioning, verifying, and revising information. Current evidence suggests that note-taking remains educationally valuable relative to LLM-only learning and that learner–AI collaborative note-making may offer stronger outcomes than passive AI-generated notes.

The overall conclusion is that deep comprehension is produced not by the digital notebook itself, but by the intellectual operations the learner performs through it. Effective digital note-taking should therefore move students from recording information toward restructuring knowledge and from rereading notes toward retrieving ideas. Future empirical research should compare different digital strategies using delayed conceptual tests, analyze the relationship between note quality and retrieval behavior, investigate stylus, keyboard, voice, and multimodal input, and determine how AI assistance changes learner attention, metacognitive judgment, and durable understanding.

References

1. Mueller, P. A., & Oppenheimer, D. M. (2014). The pen is mightier than the keyboard: Advantages of longhand over laptop note taking. *Psychological Science*, *25*(6), 1159–1168. https://doi.org/10.1177/0956797614524581
2. Morehead, K., Dunlosky, J., Rawson, K. A., Blanchard, J. L., & Doughty, E. L. (2019). Note-taking habits of 19,155 college students: Implications for student learning. *Educational Psychology Review*, *31*, 179–195. https://doi.org/10.1007/s10648-018-9458-3
3. Kobayashi, K. (2005). What limits the encoding effect of note-taking? A meta-analytic examination. *Contemporary Educational Psychology*, *30*(2), 242–262. https://doi.org/10.1016/j.cedpsych.2004.10.001

4. Kobayashi, K. (2006). Combined effects of note-taking/reviewing on learning and the enhancement of delayed retention: A meta-analytic review. *Educational Psychology, 26*(4), 459–477. https://doi.org/10.1080/01443410500342070
5. Piolat, A., Olive, T., & Kellogg, R. T. (2005). Cognitive effort during note-taking. *Applied Cognitive Psychology*, *19*(3), 291–312. https://doi.org/10.1002/acp.1086
6. Kiewra, K. A. (1985). Investigating note-taking and review: A depth of processing alternative. *Educational Psychologist, 20*(1), 23–32. https://doi.org/10.1207/s15326985ep2001_3
7. Kiewra, K. A. (1989). A review of note-taking: The encoding-storage paradigm and beyond. *Educational Psychology Review*, *1*, 147–172. https://doi.org/10.1007/BF01326640
8. Di Vesta, F. J., & Gray, G. S. (1972). Listening and note taking. *Journal of Educational Psychology, 63*(1), 8–14. https://doi.org/10.1037/h0032242
9. Bretzing, B. H., & Kulhavy, R. W. (1979). Notetaking and depth of processing. *Contemporary Educational Psychology, 4*(2), 145–153. https://doi.org/10.1016/0361-476X(79)90021-4
10. Einstein, G. O., Morris, J., & Smith, S. (1985). Note-taking, individual differences, and memory for lecture information. *Journal of Educational Psychology*, *77*(5), 522–532. https://doi.org/10.1037/0022-0663.77.5.522
11. Fisher, J. L., & Harris, M. B. (1973). Effect of note taking and review on recall. *Journal of Educational Psychology, 65*(3), 321–325. https://doi.org/10.1037/h0035640
12. Hartley, J., & Davies, I. K. (1978). Note-taking: A critical review. *Programmed Learning and Educational Technology, 15*(3), 207–224. https://doi.org/10.1080/1355800780150307
13. Peverly, S. T., Reddington, L. A., Sumowski, J. F., Johnson, K. L., & Parsons, L. (2013). What predicts skill in lecture note taking? *Journal of Educational Psychology, 105*(2), 478–493. https://doi.org/10.1037/a0032002
14. Mueller, P. A., & Oppenheimer, D. M. (2018). Technology and note-taking in the classroom, boardroom, hospital, and courtroom. *Trends in Cognitive Sciences, 22*(7), 545–547. https://doi.org/10.1016/j.tics.2018.04.002
15. Bui, D. C., Myerson, J., & Hale, S. (2013). Note-taking with computers: Exploring alternative strategies for improved recall. *Journal of Educational Psychology, 105*(2), 299–309. https://doi.org/10.1037/a0030367
16. Luo, L., Kiewra, K. A., Flanigan, A. E., & Peteranetz, M. S. (2018). Laptop versus longhand note taking: Effects on lecture and self-regulated learning. *Educational Psychology, 38*(9), 1149–1168. https://doi.org/10.1080/01443410.2018.1499292
17. Aiken, K. M., Thomas, G. S., & Shennum, W. A. (1975). Memory for a lecture: Effects of note-taking and review. *Journal of Educational Psychology, 67*(3), 439–444. https://doi.org/10.1037/h0076623
18. Mueller, P. A., & Oppenheimer, D. M. (2014). The impact of laptop note-taking on students' learning and comprehension. *Psychological Science, 25*(6), 1159–1168.
19. 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
20. Mayer, R. E. (2008). Applying the science of learning: Evidence-based principles for the design of multimedia instruction. *American Psychologist, 63*(8), 760–769. https://doi.org/10.1037/0003-066X.63.8.760