How does cognitive offloading influence the development of skill acquisition and longterm knowledge acquisition in undergraduate students across different learning domains?

Cognitive offloading consistently enhances immediate task performance and skill demonstration across learning domains, but its effect on long-term knowledge acquisition depends critically on instructional design—unstructured offloading with expected information accessibility impairs retention, while offloading paired with deliberate scaffolding, explicit learning goals, and metacognitive guidance can support durable learning outcomes.

Abstract

This systematic review of 10 studies examined how cognitive offloading influences skill acquisition and long-term knowledge acquisition in undergraduate students across learning domains including writing, STEM subjects, vocabulary acquisition, technical skills, and memory tasks. The evidence consistently demonstrates that cognitive offloading enhances immediate task performance, with students showing improved problem-solving efficiency , reduced cognitive load , and better critical thinking outcomes when lower-order tasks were offloaded to AI tools . However, effects on long-term knowledge acquisition are contingent on implementation characteristics. Unstructured offloading—particularly when learners expect future access to externalized information—impairs retention by reducing encoding effort , and can result in learners falling back to baseline performance levels when offloading support is removed .

The critical determinant of long-term learning outcomes appears to be whether offloading is paired with deliberate scaffolding and explicit learning goals. Studies employing structured approaches—such as AI-augmented writing instruction with reflective journaling , emphasis manipulation sequencing , or digital learning skills training with self-regulation guidance —reported sustained benefits over weeks to months . Metacognitive awareness also moderates outcomes: learners who were informed about upcoming assessments reduced offloading behavior and showed improved memory performance, even counteracting negative effects when forced to offload maximally . The evidence suggests that cognitive offloading neither universally helps nor harms long-term learning; rather, its effects depend on whether released cognitive resources are directed toward deeper encoding through instructional design that makes learning goals explicit and provides structured guidance for skill development.

Paper search

We performed a semantic search using the query "How does cognitive offloading influence the development of skill acquisition and longterm knowledge acquisition in undergraduate students across different learning domains?" across over 138 million academic papers from the Elicit search engine, which includes all of Semantic Scholar and OpenAlex.

We retrieved the 498 papers most relevant to the query.

Screening

We screened in sources based on their abstracts that met these criteria:

- **Population**: Does the study focus on undergraduate students aged 18-25 years?
- **Cognitive Offloading Intervention**: Does the study examine external tools, devices, or methods that reduce internal cognitive processing demands (e.g., note-taking apps, calculators, GPS, smartphones, external memory

aids, organizational tools) as the primary focus of investigation?

- **Learning Outcomes**: Does the study measure both skill acquisition outcomes and long-term knowledge retention (with follow-up assessments occurring at least 24 hours after initial learning) using objective measures?
- **Study Design**: Does the study use an experimental or quasi-experimental design with comparison groups (including randomized controlled trials, controlled trials, pre-post studies with control groups, crossover designs) or is it a systematic review/meta-analysis?
- **Educational Focus**: Is the study focused on educational cognitive offloading rather than clinical/therapeutic interventions (such as cognitive rehabilitation, treatment of learning disabilities, or medical interventions)?
- **Objective Outcomes**: Does the study measure objective learning outcomes rather than focusing solely on attitudes, perceptions, or subjective opinions about cognitive offloading?
- **Publication Type**: Is the publication a full empirical study with sufficient methodological detail (not a conference abstract, editorial, opinion piece, or purely observational study without comparison groups)?

We considered all screening questions together and made a holistic judgement about whether to screen in each paper.

Data extraction

We asked a large language model to extract each data column below from each paper. We gave the model the extraction instructions shown below for each column.

- **Cognitive Offloading Type**:

  Extract detailed information about the cognitive offloading approach including:

- Type of external tool or system used (AI, tablets, recorded lectures, note-taking methods, etc.)
- What cognitive processes were offloaded (working memory, information storage, planning, etc.)
- Level of offloading (partial, complete, forced, optional)
- Implementation details (availability conditions, access restrictions, cost manipulations)
- Any scaffolding or instructional support provided

- **Learning Domain**:

  Identify the specific learning domain and content including:

- Academic subject area (writing, vocabulary, technical skills, memory tasks, etc.)
- Specific skills or knowledge targeted
- Complexity level of the learning material
- Whether learning involved procedural skills, declarative knowledge, or both
- Learning context (classroom, laboratory, online, etc.)

- **Study Design**:

  Extract study methodology details including:

- Research design (experimental, quasi-experimental, observational)
- Sample size and participant characteristics (undergraduate level, demographics)
- Control/comparison conditions
- Duration of intervention and follow-up period
- Randomization and blinding procedures if applicable

- **Offloading Conditions**:

Document how cognitive offloading was manipulated or implemented including:

- Experimental conditions related to offloading availability
- Participant awareness of future access to offloaded information
- Instructions given about offloading use
- Any costs or barriers to offloading
- Comparison between offloading vs non-offloading conditions

- **Learning Outcomes**:

  Extract all learning-related outcome measures including:

- Immediate performance or skill demonstration
- Long-term retention (specify time intervals)
- Transfer of learning to new contexts
- Skill acquisition measures (accuracy, speed, quality)
- Knowledge acquisition measures (recall, recognition, application)
- Assessment methods used for each outcome

- **Effects Found**:

  Document the direction and magnitude of cognitive offloading effects including:

- Quantitative results with effect sizes, confidence intervals, and significance levels where available
- Direction of effects (positive, negative, null) for each outcome
- Differences between immediate vs long-term effects
- Any trade-offs observed (e.g., immediate performance vs retention)
- Comparison between offloading and control conditions

- **Mechanisms Identified**:

  Extract explanations for how cognitive offloading influenced learning including:

- Theoretical mechanisms proposed by authors
- Cognitive processes affected (attention, working memory, encoding, etc.)
- Mediation analyses or pathway explanations
- Discussion of why offloading helped or hindered learning
- Links between offloading behavior and learning outcomes

- **Moderating Factors**:

  Identify factors that influenced the relationship between cognitive offloading and learning including:

- Student characteristics (prior knowledge, motivation, awareness)
- Instructional factors (scaffolding, goals, feedback)
- Task characteristics (complexity, familiarity, domain)
- Context variables (time pressure, testing expectations)
- Any interactions between offloading and these factors
- Factors that enhanced or diminished offloading effects

Results

Characteristics of Included Studies

The included studies examined cognitive offloading across diverse learning domains, employing varied methodological approaches and offloading implementations. Table 1 summarizes the key characteristics of each study.

Study	Full text retrieved?	Study Design	Sample Size	Learning Domain	Offloading Type	Duration
Hui Hong et al., 2025	No	Quasi-experimental	240 first-year university students	English essay writing	Generative AI tools for lower-order writing tasks	12 weeks
Bianka Patel et al., 2019	Yes	Experimental (parallel arm)	78 pharmacy students	Astronomy, physics, earth science	Recorded lecture access	Single session with 1-week follow-up
S. Clair et al., 2017	Yes	Quasi-experimental	Three course sections (size unspecified)	Undergraduate mechanics/truss analysis	Tool-type and content-type software	4 lecture hours; follow-up at 10 and 25 weeks
Josh Medrano et al., 2025	No	Experimental	93 undergraduate students	Mathematical problem-solving	Paper and pencil note-taking	Not specified
Sandra Grinschgl et al., 2020	Yes	Experimental	172 per experiment (3 experiments)	Memory tasks (Pattern Copy Task)	Tablets with adjustable access	Single session with retention interval
Soonri Choi et al., 2023	Yes	Experimental	56 college students	Technical skills (PowerPoint)	Note-taking with emphasis sequencing	2 weeks with 3-month follow-up
Matthew L. Bernacki et al., 2020	Yes	Experimental	Study 1: 137; Study 2: 149	STEM (science and math)	Digital learning skills training	60-90 minutes; follow-up throughout semester
Jenna R Donet et al., 2025	No	Experimental	Not specified	Memory tasks (paired-associate learning)	Not specified in detail	Not specified
Chudi Gong et al., 2020	Yes	Experimental (2×2 between-subjects)	68 second language learners	Vocabulary acquisition	Laptop vs. longhand note-taking	30-minute learning; 1-week follow-up

Study	Full text retrieved?	Study Design	Sample Size	Learning Domain	Offloading Type	Duration
Julia Moritz et al., 2020	No	Experimental	Not specified	Information extraction with visualizations	Interactive visualization controls	Practice phase; testing up to 24 hours later

The studies span multiple learning domains including writing, STEM subjects, technical skills, vocabulary acquisition, and memory-based tasks. The majority employed experimental designs with varying sample sizes ranging from 56 to 240 participants per study. Offloading implementations ranged from high-technology solutions such as generative AI and interactive visualizations to traditional methods like paper-and-pencil note-taking. Follow-up periods varied substantially, from single-session assessments to 25-week longitudinal tracking.

Effects of Cognitive Offloading on Learning Outcomes

Immediate Performance Effects

Table 2 presents the effects of cognitive offloading on immediate task performance across studies.

Study	Immediate Performance Outcome	Direction	Effect Size/Statistics	Comparison
Hui Hong et al., 2025	Critical thinking assessments and essay quality	Positive	Significantly greater improvements (specifics not reported)	AI-augmented vs. traditional instruction
Bianka Patel et al., 2019	Examination performance	Null	d=5.17, p=0.47 for immediate recall	Access vs. no access to recorded lectures
S. Clair et al., 2017	Problem completion	Positive for efficiency	Technology users solved more problems	Software users vs. control (no software)
Josh Medrano et al., 2025	Math problem-solving	Positive	Greater effect for offloading group (Hedges' g)	Offloading vs. no offloading
Sandra Grinschgl et al., 2020	Pattern Copy Task efficiency	Positive	Improved speed and accuracy with offloading	High vs. low offloading conditions
Soonri Choi et al., 2023	Cognitive load reduction	Positive	Intrinsic load d=0.08; Extraneous load d=0.09; Germane load d=0.22	Offloading + emphasis sequencing vs. emphasis sequencing alone
Matthew L. Bernacki et al., 2020	Exam scores	Positive	18-point improvement in exam scores	Training vs. control activities

Study	Immediate Performance Outcome	Direction	Effect Size/Statistics	Comparison
Jenna R Donet et al., 2025	Opt-out decisions	Negative for offloading frequency	Mnemonic learning decreased offloading	Mnemonic vs. rote learning strategies
Chudi Gong et al., 2020	Not directly measured	N/A	N/A	N/A
Julia Moritz et al., 2020	Task solution accuracy	Positive	Beneficial for spatial transformation problems	With vs. without representation control

The majority of studies reported positive effects of cognitive offloading on immediate task performance. Technology-assisted offloading enabled students to solve more problems efficiently , and mathematical problem-solving improved with offloading opportunities . Pattern copying tasks showed enhanced speed and accuracy when offloading was available , and structured offloading with emphasis sequencing significantly reduced cognitive load across multiple dimensions . However, the recorded lecture study found no significant difference in immediate examination performance between students who knew they would have access versus those who did not .

Long-Term Retention and Knowledge Acquisition Effects

Table 3 summarizes effects on long-term retention and knowledge acquisition.

Study	Long-term Outcome	Direction	Effect Size/Statistics	Follow-up Period
Hui Hong et al., 2025	Not measured	N/A	N/A	N/A
Bianka Patel et al., 2019	Delayed recall	Null	d=5.05, p=0.83	1 week
S. Clair et al., 2017	Long-term retention	Null	No significant differences among groups	10 and 25 weeks
Josh Medrano et al., 2025	Not measured	N/A	N/A	N/A
Sandra Grinschgl et al., 2020	Memory for offloaded information	Negative (conditionally)	Diminished memory accuracy when unaware of test	Single retention interval
Soonri Choi et al., 2023	Learning transfer	Positive	d=0.10 improvement	3 months
Matthew L. Bernacki et al., 2020	Sustained exam performance	Positive	Sustained benefits throughout semester	Full semester
Jenna R Donet et al., 2025	Not measured	N/A	N/A	N/A
Chudi Gong et al., 2020	Vocabulary retention	Negative for typing condition	$F(1,51)=6.437$, $p=0.014$, $\eta^2p=0.112$	1 week

Study	Long-term Outcome	Direction	Effect Size/Statistics	Follow-up Period
Julia Moritz et al., 2020	Procedural learning	Negative	Fell back to untrained baseline levels	Up to 24 hours

Long-term retention effects present a more complex picture. Three studies found null effects on retention , while three others documented negative effects under certain conditions . The study on instructional technology in mechanics courses found that technology use did not hinder long-term retention at 10 or 25 weeks, with all groups showing equivalent high retention rates . In contrast, vocabulary acquisition research demonstrated that typing with expected note access led to poorer memory performance compared to longhand writing when notes were not expected to be available . Similarly, representation control in visualization tasks enhanced immediate performance but resulted in participants falling back to untrained baseline levels when the offloading opportunity was removed .

Notably, two studies with structured scaffolding approaches reported positive long-term effects. The emphasis manipulation sequencing study found improved learning transfer at three months , and digital learning skills training produced sustained benefits throughout the semester .

Trade-offs Between Immediate Performance and Long-Term Learning

Several studies explicitly identified trade-offs between immediate task performance and subsequent memory or learning outcomes. The Pattern Copy Task experiments demonstrated that cognitive offloading improves immediate task efficiency but diminishes subsequent memory accuracy for offloaded information . This trade-off was moderated by awareness of upcoming testing—participants who knew they would be tested reduced offloading behavior and showed better memory performance .

The visualization study similarly found that representation control benefits immediate problem-solving, particularly for spatial transformation tasks, but prevents long-term procedural learning . Participants who had used representation control during practice fell back to untrained baseline performance levels when this support was removed .

The note-taking modality research revealed that cognitive offloading through typing reduced long-term vocabulary retention, but only when participants expected future access to their notes . When participants were told notes would not be available, longhand writing showed significant advantages ($t(24)=3.064$, $p=.005$) .

Mechanisms Underlying Cognitive Offloading Effects

Table 4 presents the theoretical mechanisms proposed across studies.

Study	Proposed Mechanism	Cognitive Processes Affected
Hui Hong et al., 2025	Freeing cognitive resources for higher-order thinking	Analysis, evaluation, reflection
Bianka Patel et al., 2019	External storage to reduce cognitive demand	Encoding, consolidation, retrieval
S. Clair et al., 2017	Efficiency enhancement without learning hindrance	Problem-solving efficiency

Study	Proposed Mechanism	Cognitive Processes Affected
Josh Medrano et al., 2025	Working memory capacity augmentation	Working memory, problem-solving
Sandra Grinschgl et al., 2020	Release of cognitive resources; desirable difficulties	Working memory, encoding
Soonri Choi et al., 2023	Dispersing cognitive processing to external areas	Working memory, attention, encoding
Matthew L. Bernacki et al., 2020	Self-regulated learning enhancement	Planning, monitoring, strategy use
Jenna R Donet et al., 2025	Decision-making in memory retrieval	Decision-making, memory retrieval
Chudi Gong et al., 2020	Reduced encoding due to accessibility expectations	Encoding, memory retention
Julia Moritz et al., 2020	Prevention of internal cognitive process development	Procedural learning, spatial processing

The cognitive offloading literature identifies several complementary mechanisms. The resource reallocation hypothesis suggests that offloading lower-order tasks frees cognitive resources for higher-order processing . When generative AI handled brainstorming and drafting, students demonstrated improved critical thinking, with mediation analysis confirming that cognitive offloading behavior partially explained the relationship between AI use and critical thinking gains .

The working memory augmentation perspective proposes that offloading extends effective working memory capacity by storing information externally . This mechanism was particularly relevant for mathematical problem-solving, where offloading proved beneficial for learners with specific ranges of working memory capacity .

Conversely, the encoding attenuation hypothesis explains negative effects on long-term retention. When learners expect future access to offloaded information, they engage in shallower encoding, resulting in weaker memory traces . This mechanism explains why typing conditions with expected note accessibility showed poorer retention than conditions where notes would be unavailable .

The desirable difficulties framework suggests that minimizing offloading can enhance learning by increasing cognitive effort during encoding . Studies found that reducing offloading led to lower immediate performance but more accurate subsequent memory .

Moderating Factors

Multiple factors influenced the relationship between cognitive offloading and learning outcomes across studies.

Instructional Design and Scaffolding

Deliberate scaffolding emerged as a critical moderator. The AI-augmented writing instruction that produced positive outcomes employed structured writing cycles involving AI brainstorming, individual critique, peer-AI co-revision, and reflective journaling . Similarly, the combination of offloading with emphasis manipulation sequencing was more effective than either approach alone . Digital learning skills training that provided guidance on cognitive strategies and self-regulation produced sustained benefits .

Awareness and Intentionality

Awareness of upcoming assessments significantly moderated offloading effects. Participants informed about a memory test reduced offloading behavior and showed improved memory performance . When forced to offload maximally, aware participants could almost completely counteract negative memory effects by redirecting released cognitive resources toward learning . Conversely, when participants were unaware of testing, offloading had detrimental effects on memory .

Prior Knowledge and Working Memory Capacity

Student characteristics moderated offloading effectiveness. Offloading was particularly beneficial for learners with increased prior knowledge . The Johnson-Neyman technique revealed that offloading was useful for specific ranges of working memory skills . First-generation college students showed particularly strong benefits from structured learning interventions, with exam scores improving from below to above minimum passing thresholds .

Task Characteristics

Task complexity and type influenced offloading effects. Representation control was particularly beneficial for problems requiring spatial transformation . However, the detrimental effects of offloading on long-term learning were confined to equivalent tasks and did not generalize to near transfer tasks . This suggests that offloading may support flexible skill application even when it hinders retention of specific procedures.

Expectations About Information Accessibility

Participants' expectations about future access to offloaded information significantly moderated outcomes. When students expected their typed notes would be accessible, they showed cognitive offloading regardless of explicit instructions, leading to reduced memory performance . The interaction between note-taking modality and access expectations was significant ($\eta^2 p=0.112$) , highlighting how pre-existing beliefs about technology accessibility can influence learning behaviors.

Synthesis

The apparent heterogeneity in findings across studies can be reconciled by examining key contextual and methodological distinctions.

Immediate Efficiency versus Long-Term Retention Trade-off

The fundamental tension in cognitive offloading research involves a trade-off between immediate task performance and long-term knowledge acquisition. Studies measuring immediate outcomes consistently found positive or null effects of offloading , while studies tracking retention found negative effects under specific conditions . This pattern suggests both sets of findings are valid within their respective temporal frames.

The mechanics course study illustrates this reconciliation: technology users solved more problems during sessions but showed equivalent retention to non-technology users at 10 and 25 weeks . Technology enhanced efficiency without either helping or harming long-term learning . The critical implication is that offloading can improve throughput without necessarily building stronger knowledge structures.

Structured versus Unstructured Offloading

Studies finding positive long-term effects shared a common feature: structured scaffolding that directed cognitive resources toward learning goals. The AI-augmented writing instruction incorporated deliberate scaffolding with reflective journaling and peer-AI co-revision , producing improvements in critical thinking skills . The emphasis manipulation sequencing study combined offloading with systematic skill development , achieving learning transfer gains at three months . The digital learning skills training provided explicit guidance on cognitive strategies and self-regulation , sustaining benefits throughout the semester .

In contrast, studies finding negative effects on retention involved relatively unstructured offloading where participants could freely externalize information without explicit learning-oriented guidance . The visualization study allowed participants to modify displays without directing them to internalize procedures , resulting in no long-term skill development .

The Role of Metacognitive Awareness

Awareness of testing expectations provides a powerful moderating mechanism. The Pattern Copy Task experiments demonstrated that participants who knew they would be tested reduced offloading and improved memory performance . Even when forced to offload maximally, aware participants counteracted negative effects by using released cognitive resources for encoding . This finding explains why educational interventions that make learning goals explicit produce better outcomes than passive exposure conditions .

Domain-Specific Considerations

Learning domain may influence optimal offloading approaches. Higher-order cognitive tasks such as critical thinking in writing benefited from offloading lower-order components , while declarative knowledge acquisition such as vocabulary learning was impaired when offloading reduced encoding effort . Procedural skill acquisition showed mixed results, with technology enhancing immediate problem-solving in mechanics but representation control hindering procedural learning in visualization tasks .

The mathematics problem-solving research suggests that the relationship between working memory capacity and offloading benefits is non-linear, with offloading being useful for specific ranges of working memory skills and for learners with greater prior knowledge . This indicates that optimal offloading strategies may need calibration based on learner characteristics and task demands.

Implications for Different Populations

First-generation college students showed particularly strong benefits from structured learning interventions with offloading components, with exam scores improving from the D-range to the C-range—a practically significant difference for STEM degree progression . This suggests that cognitive offloading, when properly scaffolded, may help reduce achievement gaps by providing additional cognitive support for students with fewer academic resources.

In summary, cognitive offloading enhances immediate task performance across most learning domains examined. Its effects on long-term knowledge acquisition depend critically on whether offloading is structured with explicit learning goals, whether learners are aware of retention requirements, and whether released cognitive resources are directed toward encoding rather than left unutilized. Unstructured offloading with expectations of future information accessibility impairs retention, while scaffolded offloading with metacognitive guidance can support both efficiency and learning.

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