

Spaced Repetition and Retrieval Practice: Efficient Learning Mechanisms from a Cognitive Psychology Perspective and Their Empowerment by AI

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Abstract

This paper explores two efficient learning strategies-spaced repetition and retrieval practice-from the perspective of cognitive psychology, and examines their integration with artificial intelligence (AI) technology. It first establishes the theoretical foundation by elaborating on the human memory processes (encoding, storage, retrieval), Ebbinghaus's forgetting curve, the spacing effect, and the retrieval practice effect, clarifying how these strategies align with the brain's memory mechanisms. The paper then analyzes the scientific principles of spaced repetition, including its reliance on memory consolidation theory and desirable difficulty theory, as well as the evolution of interval arrangement algorithms from fixed-interval models, e.g., Leitner System, to modern data-driven and deep learning-based systems, e.g., SSP-MMC, LSTM-HLR. For retrieval practice, it compares the cognitive differences between active retrieval and passive review, evaluates the effectiveness of different retrieval forms (free recall, fill-in-the-blank, multiple-choice), and discusses its application in teaching. Furthermore, the study emphasizes the synergistic effect of combining spaced repetition and retrieval practice (forming "spaced retrieval"). And how AI enhances these strategies-adaptive learning systems use large-scale memory data and machine learning to personalize review plans, optimize retrieval difficulty, and improve learning efficiency. Finally, the paper identifies practical challenges, e.g., initial cognitive load, personalized calibration, and proposes optimization strategies, while outlining future directions for AI-integrated learning systems. Empirical evidence throughout the paper confirms that these strategies significantly boost long-term knowledge retention compared to traditional learning methods.

Keywords

spaced repetition, cognitive psychology, adaptive learning systems

1. Introduction

Learning has never been an instantaneous process; humanity's exploration of efficient learning methods has never ceased. In today's era of information explosion, how to truly embed knowledge deep into memory has become a challenge that every learner must confront. Research in cognitive psychology has uncovered a seemingly paradoxical yet profoundly insightful principle: studies show that memory content requiring greater effort during retrieval tends to be retained for longer periods. This discovery challenges the intuitive notion in traditional learning that "repetition equals mastery", while providing a theoretical foundation for the development of scientific learning strategies. It is precisely on the basis of this discovery that "spaced repetition" and "retrieval practice"-two learning strategies-have gradually transitioned from laboratory settings to

widespread public use, evolving into effective tools against forgetting.

Spaced repetition is not merely a simple “review”, but rather a precise intervention conducted through scientifically planned time intervals just as memory is on the verge of decay. This strategy cleverly leverages the brain’s memory mechanisms—each retrieval following an interval strengthens the neural traces of the memory. Retrieval practice takes this a step further, requiring learners to actively recall information rather than passively repeating it. Although this process often accompanies a cognitive “sense of effort” and may even involve errors, it is this active construction that significantly enhances the long-term retention rate and transferability of knowledge. Underpinning these two methods are decades of cognitive psychology’s decoding of the human memory system: memory consolidation cannot be separated from the sedimentation of time and active challenges.

From Ebbinghaus’s forgetting curve to empirical studies in modern cognitive science, the effectiveness of spaced repetition and retrieval practice has been repeatedly validated. However, their potential remains underexplored by most learners. This may be because human nature tends to pursue immediate fluency—the “fluency illusion” induced by repeatedly reading notes often leads people to mistakenly believe that they have mastered the knowledge. Yet true learning occurs precisely in those moments of pausing, struggling, and even making mistakes. This article explores the scientific foundations and practical applications of these two learning strategies from the perspective of cognitive psychology, and seeks to address a fundamental question: How can learning outcomes be transformed from short-term transient performance into long-term stable accumulation? Of particular note is that, with the advancement of artificial intelligence technology, spaced repetition and retrieval practice are undergoing revolutionary changes: AI-driven adaptive learning systems not only precisely predict individual memory decay curves but also optimize the difficulty and timing of retrieval practice, thereby enabling highly personalized learning experiences.

2. Theoretical Foundations: Cognitive Psychological Mechanisms of Memory

2.1 Encoding, Storage and Retrieval of Memory

The human memory system is a complex information processing system, encompassing three basic processes: encoding, storage, and retrieval. Encoding is the initial processing and transformation of information into neural codes; storage is the maintenance of information over a period of time; and retrieval is the later access to the required information from the memory store. Research in cognitive psychology indicates that “memory strength” is not fixed but dynamically changes with time and the number of repetitions. “Memory traces” require repeated reinforcement to consolidate; otherwise, they decay over time, which is the fundamental law revealed by Ebbinghaus’s forgetting curve.

2.2 Forgetting Curve and Spacing Effect

Hermann Ebbinghaus discovered the exponential decay law of forgetting through self-experiments in 1885 (Ebbinghaus, 1885) proposing the famous “forgetting curve” model, $b = \frac{k}{(\log t)^c + k}$, where b represents the amount of memory retention, t represents time, and k and c are parameters. This discovery reveals the law of memory decay over time, providing a theoretical foundation for spaced repetition. The “spacing effect” developed on this basis indicates that, compared to massed learning, distributing learning content across multiple time periods for review can significantly enhance the retention of long-term memory. Numerous empirical studies confirm that the spacing effect has high universality, applicable to various learning tasks such as vocabulary memorization, conceptual understanding, and even skill acquisition, and demonstrates broad applicability across different age groups and educational stages.

2.3 Retrieval Practice Effect

The retrieval practice effect (also known as the testing effect) refers to the method of enhancing learning by actively attempting to retrieve information from memory, which strengthens memory even if the retrieval is unsuccessful. Compared to passive repetitive learning, retrieval practice creates stronger and more durable memory traces, improving the long-term retention rate and applicability of knowledge. Roediger and Abel

(2015) point out that the retrieval process itself is a powerful learning event that activates neural mechanisms related to memory consolidation, promoting the structured integration of knowledge.

3. Scientific Principles and Practice of Spaced Repetition

3.1 Cognitive Mechanisms of Spaced Repetition

The cognitive mechanisms of spaced repetition are based on “memory consolidation theory” and “appropriate difficulty theory”. Memory consolidation requires time to complete the strengthening of neural-level connections, while the appropriate difficulty principle indicates that learning needs a certain degree of cognitive effort to produce lasting effects. Spaced repetition arranges reviews at critical points of memory decay (i.e., moments when forgetting is imminent but has not yet fully occurred), compelling learners to exert appropriate retrieval effort and thereby maximizing the memory reinforcement effect. This strategy cleverly leverages the brain’s memory mechanisms—each retrieval following an interval strengthens the neural traces of the memory, effectively slowing the rate of forgetting and enhancing retention rates.

3.2 Optimal Interval Scheduling: From the SM-2 Algorithm to Modern Adaptive Systems

As shown in Table 1, early spaced repetition systems, such as the “SM-2 algorithm” adopted by “SuperMemo”, adjust review intervals based on fixed rules, which are effective but lack personalization. Modern adaptive systems, such as the “FSRS4Anki” and “SSP-MMC” algorithms, utilize machine learning and large-scale memory behavior data to dynamically formulate learning plans for each individual learner, significantly improving learning efficiency.

Among them, SSP-MMC (“Shortest Stochastic Path - Minimizing Memory Cost”) models review scheduling as a Markov decision process and employs a stochastic shortest path algorithm to optimize the review mechanism, achieving an average savings of 15.12% in review time while ensuring memory effects. This algorithm is based on the LSTM-HLR (Long Short-Term Memory - Half-Life Regression) model to predict dynamic changes in an individual’s long-term memory, thereby more accurately estimating memory states and planning optimal review points accordingly.

Table 1: Evolution Comparison of Spaced Repetition Algorithms

Algorithm Type	Representative System	Principle	Advantages	Limitations
Fixed Interval Algorithm	Leitner System	Moves cards based on the number of successful reviews	Simple and easy to implement	Lacks personalization
Rule Adjustment Algorithm	SM-2 Algorithm	Adjusts the next interval based on difficulty	Considers material difficulty	Fixed parameters
Data-Driven Algorithm	SSP-MMC	Stochastic shortest path optimization	Personalized and efficient	Computationally complex
Deep Learning Algorithm	LSTM-HLR	Recurrent neural network predicts memory	High prediction accuracy	Requires large amounts of data

Application Cases: Empirical studies on tools such as Anki and SuperMemo

Spaced repetition tools such as Anki and SuperMemo have been widely applied in fields like language learning and medical education. Research indicates that learners using these tools achieve memory retention rates more than double those of traditional learning methods. For instance, Duolingo’s language learning system employs an “Adaptive Spaced Repetition System” (SRS), which precisely calculates the optimal review time points for each word, boosting memory efficiency by 210%. The effectiveness of these tools is not only evident in short-term memory enhancement but, more importantly, in promoting “long-term knowledge retention”. A study by Smith and Karpicke (2021) involving college students found that those using digital flashcards for retrieval practice outperformed students who only reread materials by over 50% on delayed tests. This demonstrates that spaced repetition combined with retrieval practice generates a synergistic effect, greatly enhancing learning efficiency.

4. Cognitive Advantages and Implementation Strategies of Retrieval Practice

4.1 Retrieval Practice vs. Passive Review: Differences in Memory Strength

Retrieval practice and passive review, such as rereading notes, differ fundamentally in their cognitive mechanisms, with the former emphasizing active retrieval and reprocessing, while the latter relies on familiarity-based memory. Passive review primarily depends on “familiarity memory”, which easily generates an illusion of mastery; in contrast, retrieval practice strengthens “recollective memory”, creating deeper and more durable memory traces. A meta-analysis by Adesope (2017), encompassing studies across various disciplines and educational stages, indicates that retrieval practice improves long-term memory retention rates by an average of 30-50% compared to passive review, with this advantage being even more pronounced in delayed testing.

Neuroscience research provides biological evidence for the advantages of retrieval practice. fMRI studies have found that retrieval practice activates broader neural networks in the brain, including areas related to memory consolidation such as the prefrontal cortex and hippocampus. This activation pattern promotes memory reconsolidation, i.e., further stabilization upon reactivation, and integration, making knowledge easier to retrieve when needed.

4.2 Comparative Effects of Different Retrieval Practice Formats

As shown in Table 2, retrieval practice can take various implementation forms, including “free recall”, “fill-in-the-blank questions”, and “quizzes”. The effects of different retrieval practice formats vary across learning scenarios:

“Free recall” requires learners to recall information without prompts, most effectively promoting deep processing and structured organization of knowledge, but it places higher cognitive demands.

“Fill-in-the-blank questions” and “short-answer questions” provide partial cues, balancing retrieval difficulty and cognitive load, making them suitable for beginners and complex materials.

“Multiple-choice questions” and “recognition tests” involve lower retrieval difficulty but are still more effective than passive reading, ideal for large-scale assessments and self-testing.

Carpenter, et al. (2020) found that the effects of different retrieval formats depend on the nature of the learning material and the learner’s familiarity level. For conceptual knowledge, free recall is more effective; for factual knowledge, fill-in-the-blank and multiple-choice questions can also yield good results.

Table 2: Comparative Effects of Different Retrieval Practice Formats

Retrieval Format	Cognitive Demand	Optimal Application Scenarios	Implementation Difficulty	Memory Retention Effect
Free Recall	High	Conceptual Knowledge, Higher-Order Skills	Medium	Best
Fill-in-the-Blank / Short-Answer Questions	Medium	Factual Knowledge, Definitional Materials	Low	Very Good
Multiple-Choice Questions	Low	Large-Scale Testing, Self-Assessment	Low	Good
Concept Maps	High	Interconnections Between Knowledge, Systematic Understanding	High	Very Good

4.3 Teaching Practices Integrating Retrieval Practice

Agarwal and Roediger (2018) proposed multiple strategies for incorporating retrieval practice into middle school and university classrooms, including “mini-quizzes”, “low-stakes quizzes”, and “mind mapping”. These strategies not only enhance students’ memory performance but also cultivate “metacognitive abilities”—that is, the monitoring and regulation of one’s own learning state-enabling students to more accurately assess their learning progress.

The key to successfully implementing retrieval practice lies in creating a “supportive learning environment” that reduces students’ test anxiety. Research indicates that even non-graded formative assessments can produce significant testing effects, suggesting that teachers can incorporate more low-stakes quizzes in the classroom. This demonstrates that the benefits of retrieval practice primarily stem from the cognitive processes involved rather than the assessment itself.

5. Combined Applications of Spaced Repetition and Retrieval Practice

5.1 Cognitive Complementarity: Spaced Retrieval

The integration of spaced repetition and retrieval practice forms the “spaced retrieval” strategy, which has been widely applied in language learning and medical education. This strategy simultaneously leverages the dual advantages of time intervals and active retrieval. A meta-analysis by Pan and Rickard (2018) indicates that spaced retrieval improves outcomes by approximately 25% compared to using either strategy alone, with particularly significant advantages in long-term knowledge retention and transfer across contexts.

The cognitive advantage of spaced retrieval lies in its simultaneous optimization of the “encoding” and “consolidation” processes of memory. Retrieval practice strengthens the encoding of memory traces, while spaced repetition optimizes the consolidation process, making memories more stable and enduring. This dual optimization positions spaced retrieval as one of the most efficient learning strategies.

5.2 Technology-Assisted Learning: Algorithm Optimization and Adaptive Testing

Artificial intelligence technology is revolutionizing the implementation of spaced repetition and retrieval practice. Modern adaptive learning systems, such as “MaiMemo” and “FSRS4Anki”, utilize machine learning algorithms to analyze learners’ memory behavior data, dynamically adjusting review schedules and test difficulties.

These systems train memory models based on large-scale data; for instance, the SSP-MMC algorithm uses 220 million memory behavior records to construct memory models, enabling more accurate prediction of each learner’s forgetting curve and thereby facilitating the development of personalized review plans. Gervais and Baker (2021) point out that machine learning-driven adaptive systems can reduce unnecessary reviews by 15-20% while improving long-term memory retention rates by approximately 10-15%.

IBM’s latest patent technology, “Weight Repetition on RPU Crossbar Switch Arrays”, optimizes the efficiency of neural network weight repetition, accelerating the AI training process. Such technologies can also be applied to optimize large-scale computations in spaced repetition algorithms. This demonstrates the ongoing deepening of the integration between AI technology and learning sciences.

6. Challenges and Optimization Strategies in Practical Applications

Despite the evident advantages of combining spaced repetition and retrieval practice, their practical implementation still faces several challenges:

1. The so-called “initial cognitive load” refers to the psychological pressure felt by learners in the early stages due to the additional effort required: retrieval practice and spaced repetition are more “effortful” than passive learning in the initial phase, which can easily lead to frustration and hinder long-term persistence.
2. “Personalized calibration”: There are vast differences in memory abilities and knowledge backgrounds among learners, necessitating the construction of precise individual memory models through large-scale behavioral data and individualized parameters.
3. “Implementation consistency”: Spaced repetition requires long-term adherence to yield effects, and many learners struggle to maintain regular study habits.
4. “Material adaptability”: Knowledge from different disciplines may require tailored intervals and retrieval strategies.

In response to these challenges, educators and technology developers have proposed various optimization

strategies: In the early stages of learning, visual progress bars and difficulty prompts can be used for guidance and expectation management to help learners understand the value of “desirable difficulties”; “gamification elements” and “social learning” can be incorporated to enhance motivation; and more precise “personalized algorithms” can be developed to reduce initial cognitive load.

AI-Enhanced Spaced Repetition Systems: Algorithmic Advances and Adaptive Learning

AI-enhanced spaced repetition systems significantly improve learning efficiency by analyzing large-scale memory behavior data, optimizing machine learning algorithms, and enabling real-time adaptive adjustments. Their core advantages include accurately predicting individual memory states and dynamically optimizing review schedules. For example, the LSTM-HLR model can substantially reduce prediction errors, while scheduling based on the stochastic shortest path algorithm (SSP) achieves long-term memory cost minimization.

In terms of retrieval practice, AI can personalize the format, difficulty, and content of exercises, implementing adaptive difficulty adjustments to keep the retrieval process within the “desirable difficulty” range, thereby enhancing learning motivation and efficiency. The system can also recommend appropriate exercise formats based on knowledge types and provide real-time feedback and error analysis to reinforce correct memories.

Future developments in AI learning systems may incorporate multimodal data fusion, e.g., integrating voice, visual, and physiological signals, cross-domain transfer, automatic content generation, and affective computing to achieve more comprehensive personalized adaptive learning. However, attention must also be paid to ethical and social issues such as data privacy, algorithmic fairness, and the digital divide.

Future research directions include: exploring the neural mechanisms of spaced repetition and retrieval practice; developing cross-cultural adaptive systems; expanding their applications in lifelong learning; and strengthening research on technology ethics and equity. AI technology is driving spaced repetition and retrieval practice toward more efficient and personalized directions, paving the way for building smarter and fairer educational ecosystems.

7. Conclusion

This paper systematically confirms the scientific validity and practical value of spaced repetition and retrieval practice as evidence-based learning strategies, rooted in decades of cognitive psychology research on human memory. By leveraging the spacing effect and retrieval practice effect, these strategies address the core challenge of combating forgetting, effectively transforming short-term memory into long-term, stable knowledge accumulation—an advantage supported by empirical studies showing that learners using these methods, e.g., via Anki, Duolingo, to achieve 2-3 times higher memory retention rates than those relying on passive review.

The integration of AI technology marks a revolutionary advancement in these strategies. Modern adaptive systems, e.g., FSRS4Anki, SSP-MMC, overcome the limitations of early one-size-fits-all models by using machine learning and large-scale memory data, e.g., 220 million records for SSP-MMC, to accurately predict individual forgetting curves, optimize review intervals, and tailor retrieval difficulty. This personalization not only reduces unnecessary review time by 15–20% but also increases long-term retention by 10–15%, demonstrating the synergistic potential of learning science and AI.

However, practical application still faces hurdles, such as initial cognitive load that may deter learners, the need for precise personalized calibration, and consistent long-term implementation. Addressing these requires a combination of instructional guidance (e.g., expectation management), motivational design (e.g., gamification), and more refined algorithms.

Looking ahead, the future of these strategies lies in the deeper integration of AI—including multi-modal data fusion (voice, visual, physiological signals), affective computing, and automatic content generation—to build more comprehensive adaptive learning systems. Simultaneously, attention must be paid to ethical issues like data privacy and algorithm fairness to ensure equitable access to these efficient learning tools. Ultimately, spaced repetition and retrieval practice, empowered by AI, hold great promise for constructing an intelligent, personalized, and fair educational ecosystem, driving a paradigm shift from traditional massed, passive

learning to adaptive, active learning.

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Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.

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