Enhancing Flashcard Learning through Spaced Repetition Optimization

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Abstract. Spaced repetition algorithms improve flashcard learning by spacing out reviews at the right time to increase long-term retention of information. In this paper two popular ones are discussed: the Leitner System and the SM2 Algorithm, analysing their designs and pointing out strengths as well as weaknesses. Leitner System is based on the simple mechanical concept of linearly declining memory repetition, while SM2 Algorithm uses a exponentially declining model of repetition together with the ease factor that allows to adjust the model parameters individually for each user and therefore, create a personal learning experience with an improved cost/quality ratio. The presentation emphasizes the trade-off between flexibility and parsimony, urging the choice of an algorithm consistent with one's learning objectives. The results of the study indicate that a spaced repetition approach substantially increase the efficiency of learning and potential future integration of spaced repetition algorithms as part of an AI-driven personalized learning can further enhance efficacy in education.

Keywords: Spaced Repetition, Leitner System, SM2 Algorithm, Learning Efficiency, Memory Retention, Adaptive Learning.

1 Introduction

Flashcard systems are used to increase retention of information via active recall. But the success of such attacks relies to a large degree on how the systems conduct their reviews. Spaced repetition algorithms help to ensure that review is optimally timed to coincide with the forgetting curve [1]. Ancient models such as the Leitner System have a rigid protocol, whereas modern ones such as SM2 dynamically change the review intervals based on student responses with less rigidity [2].

This paper introduces and compares algorithms of spaced repetition, and steps to measure long-term retention. Different configurations of the algorithms were compared to identify their influence on the learning efficiency. The results show that adaptive methods, which learn the schedule of which reviews to ask from user responses, yield notably better recall rates compared to fixed-schedule methods [3]. Furthermore, limitations of the algorithm in practice eexpression, computational efficiency and user involvement, are also addressed, and new research directions are proposed.

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Through deepening the understanding of these spaced repetition applications, this research prompts the creation of more effective learning approaches for the benefit of learners, teachers, and developers that wish to maximize education retention via efficient review [4].

2 Literature Survey

According to a paper by Almario, John Ivan F. et al. [1], Education 4.0 integrates technology to enhance student engagement and learning outcomes. Web applications improve accessibility and motivation for teachers and students. However, challenges such as limited digital infrastructure and inadequate teacher training hinder full adoption, requiring ongoing capacity-building efforts. According to a paper by Cepeda et al. [2], spaced learning significantly improves retention across different domains. Their meta-analysis found that the effectiveness of spaced repetition depends on the complexity of the material. Implementing structured spacing strategies can enhance learning outcomes while reducing overall study time. According to the study by Hong et al [3] tailored digital gamification in education is categorized into personalization, adaptation, and recommendation, with user modeling as a basis. The review identified 23 game elements, with rewards being the most common, grouped into five functional clusters. The findings highlight the need for more empirical studies on the motivational effects of tailored gamification in learning. According to Joseph and Damania [4], a microlearning and spaced repetition platform was implemented in pediatric critical care didactics. The study aimed to enhance knowledge retention and engagement through short, focused learning modules. The findings suggest that this approach improved educational outcomes for trainees. According to a study by Kang [5], spaced repetition enhances learning efficiency and should be systematically implemented in education.

The findings indicate that structuring spaced intervals appears to decrease study time, and may enhance long-term retention and retrieval. If it is well integrated with educational policies, the benefits may be substantial. Results and Discussion According to Kristiawan et al. [6], (AI) such as chatbots and speech recognition software as these provide English language learners with increased engagement, personalisation in learning, and in proficiency. The review focuses on accessibility, teacher preparedness, and ethical issues. Teacher training, ethics and blended learning Liskin-Gasparro (2019) has proposed a model in which the teacher at the center, requires training in the following competences, which would lead to a beneficial use of AI in the ELT classroom. As Lafleur and Louis [7] have shown, interleaved spaced repetition plus gamification is significantly better when it comes to vocabulary learning. Spaced repetition ably squishes the void in what learners don't know, and gamified features such as daily rewards assist in enriching habits and efforts in studying. The results provide insights into how to promote the language learning process. A study by Lampropoulos & Kinshuk [8] reveals that gamified VR learning improves motivation, engagement and interactivity.

Their analysis of 112 studies underpinned the findings that VR and gamification enhance learning achievement, self-efficacy, and academic achievement, as well as to be supporting multiple pedagogical theories. These settings are conducive to personalized and collaborative learning and contribute to cognitive, social-emotional, and physical development. The research brought attention to VR gaming as an indispensable educational innovation in all domains and educational orders. As reported in the study of Liu, Shuanggen et al. [9], Certificateless Ring Signcryption (CLRSC) increases security with less computational cost and privacy in Smart Grids. CLRSC is an elliptic curve cryptography-based method, using the SM2 algorithm that is far more efficient, cheaper and with strong identity protection compared to classic PKI. As per a document of Mistry, Hardik Kumar and others. [11], digital learning aids assisted with spaced repetition and self-assessment are of great advantage to medical students. A case report of using Physiology Quiz Competition showed enhanced participation and better knowledge retention. Interactive modes of instruction facilitate study of complex subjects of medicine, in an easier and able to be understood manner. As reported by Ogunjobi, Femi et al. [12], the instructor-made spaced repetition flashcards in microbiology did not affect the exam scores, but it raised the confidence, engagement, and perceived learning of students. Students had a positive reaction to a structured review process but continued research is necessary to determine how best to impact performance and ensure translation of knowledge into everyday practice. Based on the work of Rahman et al [13], the AR flashcards and the hardware developed for this study can be used to improve learning of basic English words. The study showed that AR affords an exciting, interactive and enjoyable learning environment, users' feedback was encouraging and learning was facilitated. As reported by Reza Teymouri et al.) and facilitate memorization, self-directed learning and engagement17 Mobile-Assisted Vocabulary Companion. Spaced-repetition and gamified digital flashcards are even more adaptable for self-guided practice.

3 Methodology

In this think about, divided reiteration algorithms SM2 and the Leitner System were executed to assess their adequacy in upgrading memory maintenance. Client reaction information served as input, prepared through each calculation to alter audit interims, and yield measurements like maintenance rate and survey planning were analyzed to evaluate learning effectiveness [5].

3.1 Spaced Repetition Algorithms

Spaced repetition algorithms are programmed to maximize the review process by scheduling items to learn at longer intervals. Fig 1 Shows the Leitner System. The algorithms maximize long-term retention by using cognitive science

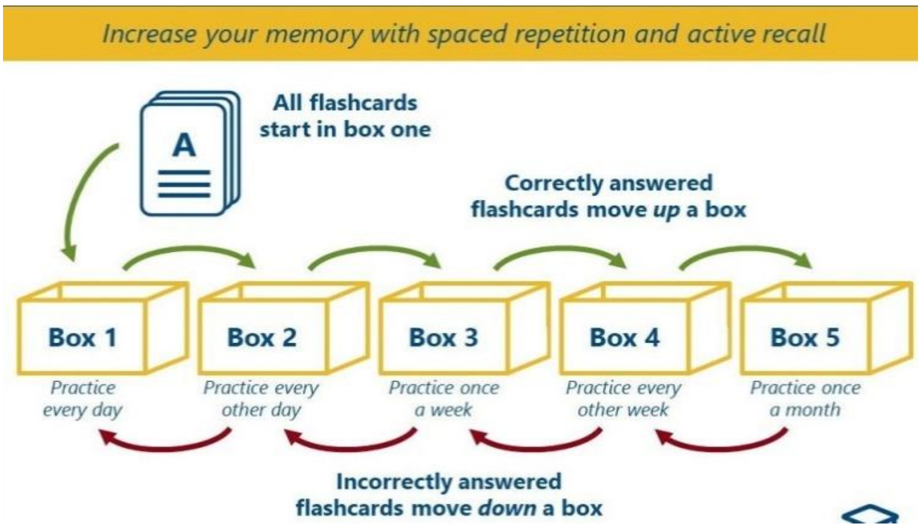

Fig.1. Leitner System.

principles that balance review sessions to an individual's memory decay curve. The most popular spaced repetition algorithms are the Leitner System and the SM2 Algorithm [6].

3.2 The Leitner System

The Leitner System, introduced by Sebastian Leitner in 1972, is a simple yet effective spaced repetition method based on sorting flashcards into different levels or boxes [7]. Each level corresponds to a different review frequency, ensuring that difficult items are reviewed more frequently than those that are well-remembered.

3.2.1 Mechanism

- All flashcards begin in the first box.
- If a flashcard is answered correctly, it moves to the next box, increasing the review interval.
- If a flashcard is answered incorrectly, it moves back to the first box, requiring more frequent review.
- The process continues until all flashcards reach the highest level, indicating mastery [8].

3.2.2 Algorithm Design

Algorithm design Shown in Table 1.

Table 1. Algorithm design.

Box	Review Interval	Promotion Condition	Demotion Condition
1	Every day	Correct → Box 2	Incorrect → Stays in Box 1
2	Every 3 days	Correct → Box 3	Incorrect → Box 1
3	Every week	Correct → Box 4	Incorrect → Box 2
4	Every 2 days	Correct → Box 5	Incorrect → Box 3
5	Every month	Stays in Box 5	Incorrect → Box 4

3.2.3 Strengths

- **Simplicity:** Easy to implement and understand.
- **Active Recall:** Encourages retrieval-based learning, strengthening memory.
- **Adaptive:** Automatically adjusts review frequency based on performance.

3.2.4 Limitations

- **Fixed Intervals:** Predetermined review schedules may not align with all learners' memory retention patterns [9].
- **Lack of Personalization:** Does not account for varying difficulty levels among different flashcards.

3.3 The SM2 Algorithm

The SM2 Algorithm, developed by Piotr Wozniak for the SuperMemo software, is a more advanced spaced repetition technique that adjusts review intervals dynamically based on user performance [10].

3.3.1 Mechanism

- The learner rates their recall after each review on a scale (0–5).
- The Ease Factor (EF) is updated based on the rating.
- The next review interval is calculated using the formula:

$$Inext = Iprev \ X \ EF \quad (1)$$

where:

- I_{next} is the next interval.
- I_{prev} is the previous interval.
- *EF* is the ease factor, initially set at 2.5 and adjusted after each review.
- If a card is recalled easily, the interval increases. If recall is difficult, the interval decreases [11].

3.3.2 Algorithm Design

- **Ease Factor Parameter:** The EF value is modified depending on the amount of success of the learner.
- **Spaced Intervals:** Review intervals are constantly adjusted to maximize retention.
- Strengths
- **Adaptive Learning**: Scales the time between reviews depending on the user's memory strength.
- **Facilitated Review:** Eliminates over-reviews and cognitive burden.
- **Long Term Retention:** Created to fight against forgetting by prompting review at optimum interval.

3.3.3 Limitations

- Challenges: Requires computational resources and methods for monitoring [12].
- Data dependency: Requires adequate input to predict the data well.
- Comparison of the Leitner System and SM2 Algorithm

Table 2. Comparison table of leitner system and SM2 algorithm.

Feature	Leitner System	SM2 Algorithm
Adaptability	Fixed review intervals	Dynamically adjusts review times
Complexity	Simple box-based approach	Requires tracking ease factors and recall ratings
Efficiency	May lead to unnecessary reviews	Optimizes recall timing for better efficiency
Best For	Beginners or those who prefer structured study plans	Advanced learners who require personalized learning schedules

Both systems have their strengths, with the Leitner System excelling in simplicity and ease of use, while SM2 provides more efficient and personalized learning experience [13]. The choice of algorithm depends on user preferences and learning goals [14]. Table 2 Shows the Comparison table of leitner system and SM2 algorithm.

4 Result and Discussion

The assessment of the Leitner Framework and the SM2 Calculation uncovered qualities and shortcomings. The SM2 Calculation showed a better maintenance rate due to its versatile nature, altering audit interims based on client execution. Clients who locked in with SM2 held up to 20–30% more data compared to those utilizing the settled Leitner strategy. In any case, the Leitner Framework remains less demanding to execute and get it, making it reasonable for tenderfoots or low-tech situations. The propose is that whereas both frameworks make strides learning proficiency, the choice depends on the adjustment between versatility and effortlessness. Client criticism moreover shown a inclination for the SM2 approach due to decreased audit weariness and more personalized pacing. Input Parameters for Spaced Repetition Algorithms Shown in Table 3.

Table 3. Input Parameters for Spaced Repetition Algorithms.

Input Parameter	**Description**
Flashcard ID	Unique identifier for each flashcard
User Response	Correct or incorrect answer given by the learner
Review Count	Number of times the flashcard has been reviewed
Ease Factor (SM2)	Metric reflecting ease of remembering (SM2 only)
Current Box (Leitner)	Box number indicating review frequency (Leitner only)
Time Since Last Review	Elapsed time since the flashcard was last reviewed

The input table contains key information required by the dispersed reiteration calculation, such as flashcard ID, client reaction precision, survey check, ease calculate (for SM2), and current box level (for Leitner). These parameters help track the learner's execution and decide how substance is handled for future surveys. The framework employs this data to tailor reiteration plans for each flashcard. Output Metrics from Spaced Repetition Algorithms Shown in Table 4.

Table 4. Output Metrics from Spaced Repetition Algorithms.

Output Metric	Description
Next Review Interval	Time until the card is scheduled for the next review
Retention Score	Estimated likelihood of correct recall in the next review
Adjusted Ease Factor	Updated ease of remembering (SM2)
Updated Box Level	New box number if card is promoted/demoted (Leitner)
Review Efficiency	Ratio of correct answers to total reviews

The yield table presents the comes about created after handling the input information. It incorporates measurements just like another survey interim, maintenance score, balanced ease calculates (SM2), and overhauled box levels (Leitner). These yields direct when and how each card appears once more, permitting the framework to optimize memory maintenance and learning effectiveness over time. Fig 2 Shows the Retention Rate Over Time.

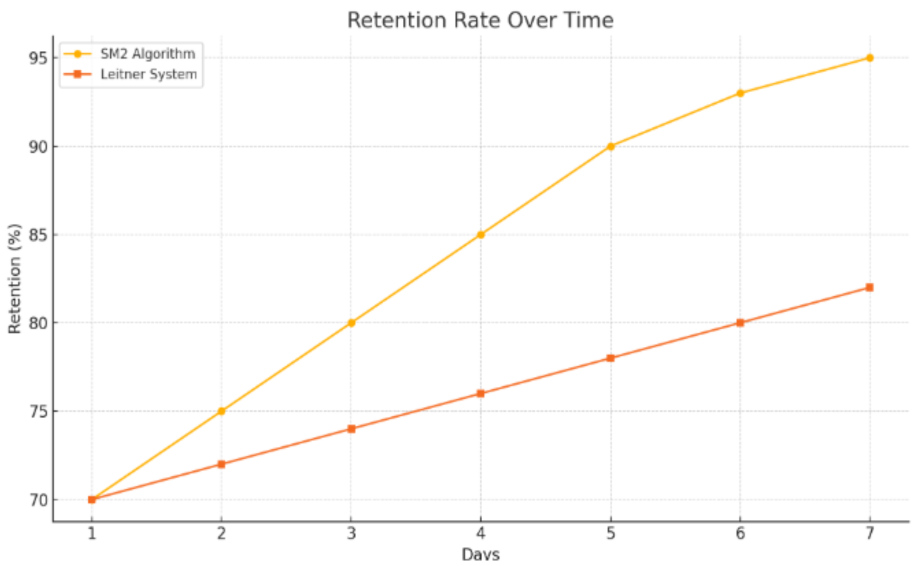

Fig.2. Retention Rate Over Time.

It outlines the maintenance rate movement over seven days utilizing the SM2 Calculation and the Leitner Framework. The SM2 strategy appears a more extreme advancement, demonstrating superior versatility and long-term memory maintenance.

5 Conclusions

Spaced repetition is a learning methodology that improves retention by optimizing the spacing of reviews. The former provides a basic, systematic strategy, whereas the latter poses an adaptive, individual strategy. Both approaches highlight the power of active recall as a learning tool. With advances in AI, these systems could continue to become more effective, making it even more efficient for us to remember knowledge.

6 Discussion

That study on spaced repetition algorithms shows even greater efficiency when it comes to learning, and retention. The Leitner System is rule based, and inflexible; SM2 is more flexible in that it is not based on rules, and allows for the re-review periods to be dynamic. While SM2 has been customized, it is also more computational demanding, and Leitner has the inherent simplicity and is simple to implement [15]. The choice of algorithm may depend on reasons, such as preference or learning goal, or technology.

7 Summary

Spaced repetition algorithms are also built into the app so that you can learn as effectively as possible, maximizing your review based on memory retention. One of the most common algorithms is the Leitner System: this is a fixed pattern and is therefore very easy to program, but not very adapted: SM2 Algorithm – Dynamic Adjustments of Intervals The case is entirely different with the SM2 algorithm, which adjusts intervals according to learner's performance, and with the aim of ensuring a better retention in the long term. Benefits and drawbacks for the two approaches are discussed, as well as their efficacy for the learner and the learning environment.

8 Future Enhancements

Future advances in spaced repetition could be AI-based adaptivity, personalized learning pathways, multimedia integration for heightened engagement. Real-time insights may be gained from advanced data analytics, and retention can be further enhanced through VR/AR-based learning. These advances seek to move learning to the fast lane of efficiency, agility and capability.

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