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Simulation and Optimization of Review Intervals Based on the Mathematical Model of the Ebbinghaus Forgetting Curve

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Abstract

Humans naturally experience memory decay over time due to the brain's limited capacity, a phenomenon first systematically quantified by Hermann Ebbinghaus in 1885 through the forgetting curve, which illustrates the exponential decline of retention in the absence of reinforcement. This curve demonstrates that newly acquired information fades rapidly unless reviewed, negatively affecting educational outcomes as students struggle to retain knowledge in the long term. Spaced repetition, involving scheduled review sessions, has emerged as an effective strategy to counteract forgetting; however, optimal review intervals are often determined intuitively rather than derived mathematically. This study aims to model memory retention dynamics using an extended Ebbinghaus forgetting curve formulated through a learning and forgetting differential equation model, estimate parameters from empirical data, and optimize review intervals to enhance long-term retention. Data were collected through questionnaires from 15 students in the 2023 Mathematics Study Program at Andalas University enrolled in Real Analysis I, yielding parameter estimates of learning rate ($\alpha = 0.70$), forgetting rate ($\lambda = 0.30$), initial knowledge level ($K(0) = 100\%$), and maximum knowledge capacity ($K\_max = 100\%$). The model was solved analytically, and numerical simulations compared three strategies: no review, random review, and optimal review at an 80% retention threshold. The optimal review time was found to be $t = 1.098$ days (approximately 26 hours and 32 minutes), corresponding to the point at which retention declines to 80%. Simulations showed that no review leads to near-zero retention over time, random review produces inconsistent improvements, and the optimal review strategy maintains retention above 80% efficiently. Overall, the mathematically derived optimal review strategy significantly outperforms alternative approaches, providing a personalized, evidence-based method to improve learning efficiency and long-term memory stability while demonstrating the value of integrating psychological memory theory with mathematical optimization for practical educational applications.

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I. INTRODUCTION

Humans naturally experience the process of forgetting over time due to their limited and fragile memory capacity. The human brain tends to filter information by only storing information that is considered important, while other information gradually fades away. This phenomenon is a natural process that was studied by Hermann Ebbinghaus in 1885 through experiments on human memory [1], [2]. His research results gave birth to the concept of the forgetting curve, where memory retention shows a gradual decline after the learning process [2]. The forgetting curve also indicates that new knowledge will experience memory decay within days or weeks, unless the material studied is repeated [3].

In the context of education, students often find it difficult to maintain their understanding of learning material. Over time, material that has been mastered tends to be forgotten if it is not studied again. One approach to overcoming this decline in memory is to repeat the material at certain intervals, known as spaced repetition [4]. This method has been empirically proven to improve retention and learning efficiency [5]. However, determining the right time to review is often still done based on estimation alone.

Several recent studies have explored mathematical models to address memory retention and spaced repetition. For instance, Murre and Dros (2015) replicated Ebbinghaus' original experiments, confirming the exponential decay and analyzing fits with power and exponential functions, while noting potential sleep-related boosts in retention [6]. Tabibian et al. (2019) developed a stochastic framework for optimizing spaced repetition using temporal point processes and stochastic differential equations, deriving optimal schedules that maximize recall while minimizing review frequency [7]. Similarly, Settles and Meeder (2016) proposed a trainable half-life regression model for language learning, predicting recall probabilities to schedule reviews adaptively [8]. Reddy et al. (2016) introduced an unbounded learning model for optimal scheduling, emphasizing queueing networks for flashcard reviews [9]. Ye et al. (2022) and (2023) advanced this with stochastic shortest path algorithms and dynamic memory capture, achieving significant improvements in review efficiency [10], [11]. Kline (2025) extended forgetting curves to neural networks, showing human-like decay and benefits from spaced reviews [12].

Despite these advancements, gaps remain in applying these models to specific educational contexts with empirical parameter estimation from small student cohorts. Previous works often rely on large datasets from apps like Duolingo [7], [8] or simulate general scenarios [9], [10], but lack focus on university-level courses like Real Analysis, where abstract mathematical concepts demand tailored retention strategies. Our study's uniqueness lies in using questionnaire-derived parameters from 15 Mathematics students, enabling individualized modeling, and comparing three practical scenarios (no review, random, optimal) through simulations. This approach bridges theoretical models with classroom application, differing from prior research by emphasizing parameter estimation from targeted surveys rather than aggregated app logs, and quantifying strategy effectiveness via retention stability metrics. Unlike Tabibian et al.'s general optimization [7], we incorporate course-specific initial knowledge assumptions, providing actionable insights for educators.

This study aims to design a more targeted and individualised learning system. Through a differential equation approach, a mathematical model was developed that can predict the time of memory decline for a particular subject and recommend the optimal time for review. The proposed model not only considers the natural process of forgetting but also individual learning abilities. With this model, it is hoped that the learning process can be optimised to provide a more effective and efficient learning experience. This study compares three learning scenarios, namely learning without review, learning with random review, and learning with review at the optimal time. The results of this study are expected to provide clear guidance on the importance of determining the right time for review in the learning process and to prove mathematically that a planned review strategy can improve long-term memory retention.

II. METHODS

This study uses a quantitative approach with mathematical modelling methods combined with primary empirical data collection through questionnaires for parameter estimation purposes [13]. This study aims to develop a mathematical model of memory retention dynamics based on the extension of Ebbinghaus's Forgetting Curve (learning and forgetting model) and to determine the optimal review time interval [6], [7].

Empirical data was obtained through a closed questionnaire distributed to 15 students of the Mathematics Study Programme at Andalas University, class of 2023, who were currently taking or had taken the Real Analysis I course. The data obtained was used to estimate the parameters in the mathematical model constructed. The stages of the research conducted were as follows:

1. Collect relevant scientific references, both books and journal articles, related to Ebbinghaus's Forgetting Curve, memory retention, and mathematical modelling of learning [6]-[12].
2. Formulate a basic mathematical model that describes the processes of learning and memory forgetting [14].
3. Develop the model by incorporating the review mechanism as a factor that influences retention dynamics [7], [8].
4. Determine model parameters based on empirical data obtained from questionnaires [13].
5. Analyse steady-state conditions to determine the long-term behaviour of the model.
6. Perform numerical simulations to describe the dynamics of memory retention over time.
7. Compare several learning strategies, namely without review, random review, and optimal review, and visualise the simulation results [10], [11].
8. Analysing and interpreting simulation results to draw conclusions regarding the effectiveness of the review strategy applied.

The method differs from previous references by focusing on a small, targeted sample for parameter estimation, unlike large-scale data mining in [7] or [8], allowing for course-specific customization while building on established differential equation frameworks [14].

III. RESULTS AND DISCUSSIONS

A. *Ebbinghaus Forgetting Curve Model*

The Ebbinghaus Forgetting Curve illustrates the decline in human memory retention over time after the learning process [15], [6]. Mathematically, this phenomenon can be modelled using the following first-order differential equation:

$$\frac{dK}{dt} = -\lambda K \tag{1}$$

where *K(t)* represents the level of memory retention at time *t*, and λ is the rate of forgetting. This model shows that memory retention decreases exponentially, where the greater the value of λ, the faster the forgetting process occurs [6].

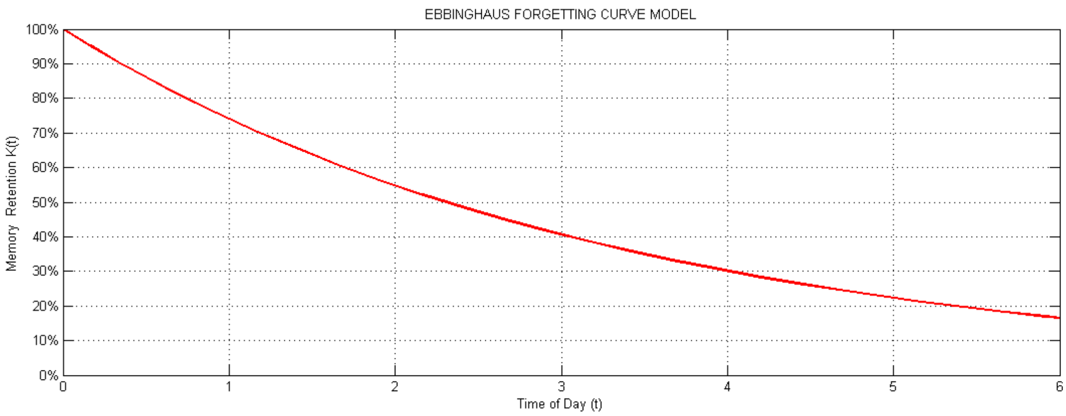

Figure 1. Ebbinghaus curve model

B. Learning and Forgetting Model

To represent the process of relearning (review), Ebbinghaus's basic forgetting curve model was expanded into a learning and forgetting model [14], [15]. This model considers two main processes, namely an increase in retention due to learning and a decrease in retention due to natural forgetting. The dynamics of memory retention are modelled as follows :

$$\frac{dK}{dt} = \alpha(K_{max} - K) - \lambda K \tag{2}$$

where K is knowledge at time t, K_{max} is the maximum memory retention limit (maximum knowledge that can be achieved), α is the learning rate, and λ is the forgetting rate. The equation can be rewritten as:

$$\frac{dK}{dt} = \alpha K_{max} - K(\alpha + \lambda). \tag{3}$$

This model can be solved using the integration method, so that the equation can be written as:

$$\frac{dk}{dt} + K(\alpha + \lambda) = \alpha\, K_{max} \tag{4}$$

with its integration factor:

$$\mu(t) = e^{\int(\alpha+\lambda)dt} = e^{(\alpha+\lambda)t}. \tag{5}$$

Then, by multiplying the integration factor to equation (4), we obtain:

$$e^{(\alpha+\lambda)t}\frac{dK}{dt} + e^{(\alpha+\lambda)t}\, K(\alpha + \lambda) = e^{(\alpha+\lambda)t}\alpha K_{max},$$

or can be written as:

$$\frac{d}{dt}\left[\, e^{(\alpha+\lambda)t}\, K\right] = e^{(\alpha+\lambda)t}\alpha\, K_{max}\,. \tag{6}$$

Next, the integration of both sides of equation (6) can be written as:

$$\int \frac{d}{dt}\left[\, e^{(\alpha+\lambda)t}\, K\right] = \int e^{(\alpha+\lambda)t}\alpha K_{max}\, dt \tag{7}$$

so that it is obtained

$$Ke^{(\alpha+\lambda)t} = \frac{\alpha K_{max}}{\alpha+\lambda} e^{(\alpha+\lambda)t} + c. \tag{8}$$

By dividing both sides of equation (8) by $e^{(\alpha+\lambda)t}$, it is obtained that

$$K(t) = \frac{\alpha K_{max}}{\alpha+\lambda} + Ce^{-(\alpha+\lambda)t}. \tag{9}$$

Equation (9) is the general solution of the learning and forgetting model from equation (2). If given the initial condition $K(0) = K_0$, then the constant C is obtained as follows:

$$C = K_0 - \frac{\alpha K_{max}}{\alpha+\lambda}. \tag{10}$$

By substituting equation (10) into equation (9), the following specific solution is obtained:

$$K(t) = \frac{\alpha K_{max}}{\alpha+\lambda} + \left(K_0 - \frac{\alpha K_{max}}{\alpha+\lambda}\right) e^{-(\alpha+\lambda)t}. \tag{11}$$

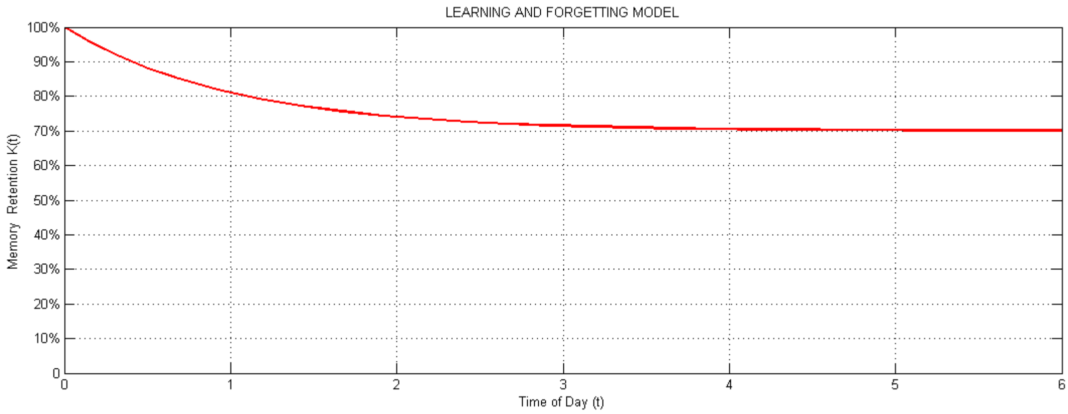

Figure 2. Learning and Forgetting Model

Based on Figure 2, this model shows that memory retention will reach a balanced value over time [14].

C. The Effect of Model Parameters on Steady State

In memory retention modelling using the learning and forgetting model, the interaction between the natural forgetting process and interventions in the form of review sessions forms a dynamic system that can reach a steady state condition [15]. This condition represents a state in which the level of memory retention no longer experiences significant changes over time, but is in a stable state. To analyse the effect of the learning rate (α) and forgetting rate (λ) parameters on this equilibrium point, changes in memory retention over time are set to zero. With this approach, the steady state expression can be derived explicitly, so that the influence of each parameter on the long-term behaviour of the system can be analysed more systematically and measurably. Thus, a steady state condition is achieved when the change in memory retention over time is zero, namely:

$$\frac{dK}{dt} = 0$$

Suppose K^* is long-term knowledge that can be retained (retention value under steady-state/equilibrium conditions). From equation (2), the steady-state condition can be written as follows:

$$\frac{dK}{dt} = \alpha(K_{max} - K^*) - \lambda K^* = 0$$

or can be written as

$$0 = \alpha K_{max} - K^*(\alpha + \lambda)$$

so that it is obtained:

$$K^*(\alpha + \lambda) = \alpha K_{max}$$

So, from the model used, the retention value under equilibrium conditions is obtained as follows:

$$K^* = \frac{\alpha K_{max}}{(\alpha+\lambda)} \tag{12}$$

Based on these results, we can conclude the influence of model parameters:

1. If the value of α is greater than λ, then the reinforcement (learning) process becomes more dominant than forgetting, so that memory retention tends to approach K_{max}. This means that the greater the learning rate compared to the forgetting rate, the closer the knowledge at time t is to the maximum knowledge capacity, so that students can remember almost all of the learning material.
2. If the value of α is smaller than λ, then forgetting becomes more dominant than the learning process, so that K(t) tends to approach zero. This means that the greater the rate of forgetting compared to the rate of learning, the more knowledge at time t approaches zero, so that students almost forget all of their learning material.

This shows the importance of balance between the rate of learning and the rate of forgetting in maintaining long-term memory, and this can be seen in figure 3 below.

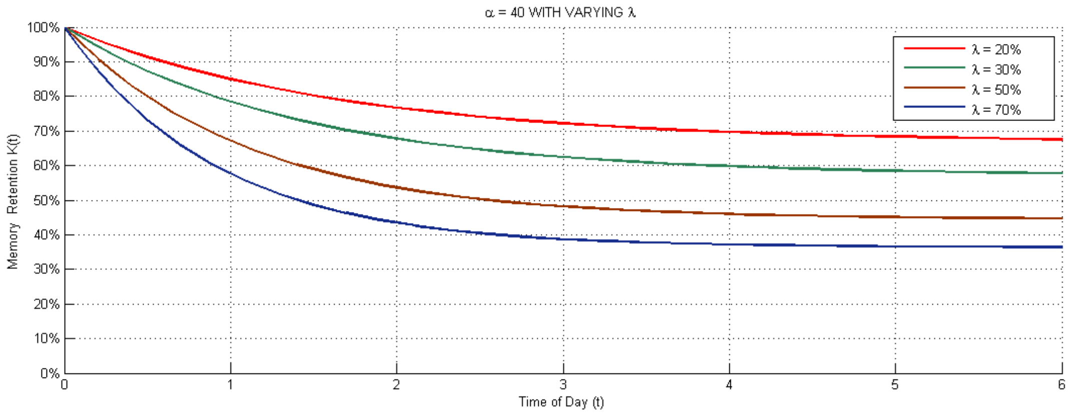

Figure 3. The Effect of Model Parameters on Steady State

D. Optimal Review Interval Formulation and Simulation

The learning and forgetting model is used to determine the optimal time to conduct a review, which is before memory retention falls below the set minimum threshold [7], [10]. In this study, the minimum retention threshold was set at 80%. Based on questionnaire data from 15 students of the Mathematics Study Programme at Andalas University, class of 2023, in the Real Analysis I course, the parameters obtained were α = 0.70 (or 70%), λ = 0.30 (or 30%), K(0) = 100% (due to prior knowledge), and K_max = 100% (because maximum memory is 100%). By substituting these values into the model in equation (11), namely

$$0.8 = \frac{0.7\times 1}{0.7+0.3} + \left(1 - \frac{0.7\times 1}{0.7+0.3}\right) e^{-(0.7+0.3)t}$$

This equation can be simplified to

$$0.1 = 0.3 \times e^{-t} .$$

by dividing both sides by 0.3, it can be written as

$$\frac{0.1}{0.3} = e^{-t} .$$

Then take the natural logarithm of both sides:

$$ln\ (0.33) = ln\ (e^{-t}) \quad ,$$

so that the following t value is obtained

$$t = 1.098.$$

Thus, the time when retention reaches 80% is obtained, which is t = 1.098 days, equivalent to approximately 26 hours and 32 minutes. This value is the optimal time interval for conducting reviews to keep memory retention at the desired level [10].

E. *Comparison of Review Strategies*

This section compares three approaches to rescheduling learning, namely no review intervals, random review, and optimal review [11]. Numerical simulations were conducted to compare these three learning strategies. The purpose of this comparison is to analyse the differences in memory retention patterns produced by each learning strategy. Through this comparison, it is possible to observe how each approach affects the stability and level of memory retention over time. Thus, this section is expected to clearly demonstrate the most effective learning strategy for maintaining long-term memory based on the results of the mathematical model simulation that has been developed.

a) Retention Without Review

Retention without review is a condition in which memory retention is allowed to decline naturally at the rate of forgetting without any repetition or reinforcement sessions. In this condition, the information that has been learned will experience a significant decline over time, making it difficult to retain in the long term. In this scenario, it is assumed that the learning process is only carried out once on day 0 and is not accompanied by subsequent review sessions.

Tabel 1. Retention Table Without Review

No.	Day (t)	Memory Retention (Knowledge at Time t)	Description
1	0	100%	Initial knowledge
2	1	74.08%	Below the target of 80%
3	2	54.88%	Far below the target
4	3	40.65%	Drastic decline
5	4	30.11%	Drastic decline
6	5	22.31%	Almost forgotten
7	6	16.52%	Starting to be forgotten

From the scenario and table 1 above, memory retention without review can be simulated in the following graph:

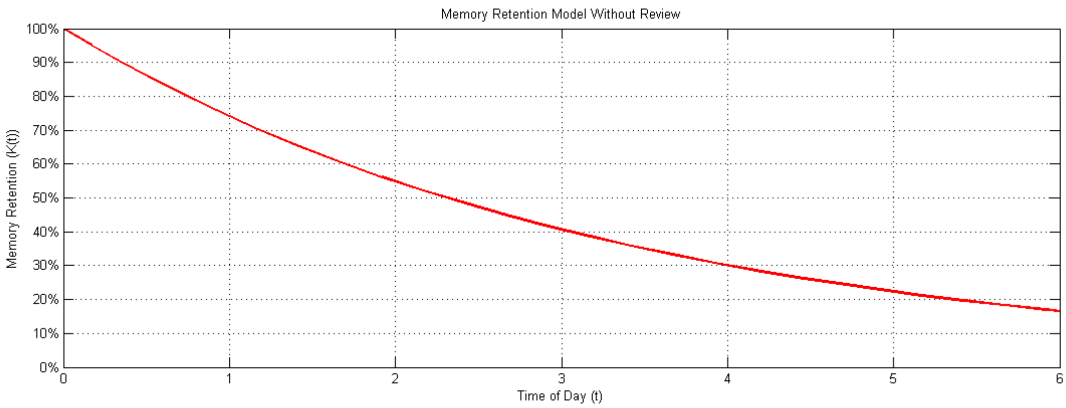

Figure 4. Memory Retention Graph without Random Review

b) Random review retention

In the random review strategy, revision sessions are conducted at irregular intervals and are not based on predictions of memory retention decline. As a result, some reviews are conducted too early when retention levels are still high, making them inefficient and potentially wasting study time, while others are conducted too late when memory retention has declined significantly. This strategy produces better retention rates than no review, but it is still unable to maintain memory retention consistently over the long term. In this scenario, reviews are conducted randomly on days 0, 1, and 6.

Tabel 2. Retention Table With Random Review

No.	Day (t)	Memory Retention (Knowledge at Time t)	Description
1	0	100%	Initial knowledge
2	1	100%	Reviewed again
3	2	81.03%	Above target
4	3	74.06%	Below target
5	4	71.49 %	Below target
6	5	70.54%	Far below target
7	6	100%	Reviewed again

From the scenario and Table 2 above, memory retention with random review can be simulated in the following graph:

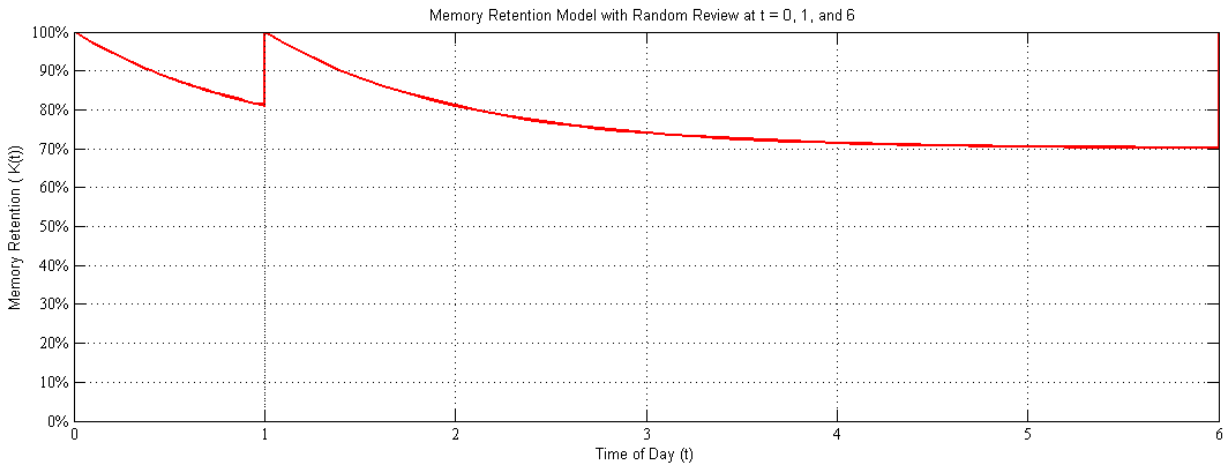

Figure 5. Memory Retention Graph with Random Reviews

c) Optimal review retention

In the optimal review strategy, each repetition session is conducted just before a significant decline in memory retention occurs. This approach produces a relatively stable retention curve, as each decline in retention is immediately corrected through a reinforcement process at the most effective time. In addition, this strategy is efficient because the number of review sessions conducted is not excessive and is focused on the most appropriate times.

Table 3. Memory Retention with Optimal Review

No.	Day (t)	Memory Retention (Knowledge at Time t)	Description
1	0	100%	Initial knowledge
2	1	80%	Reaches minimum target
3	2	100%	Reviewed again
4	3	80%	Reaches minimum target
5	4	100 %	Reviewed again
6	5	80%	Reaches minimum target
7	6	100%	Reviewed again

From the scenario and Table 3 above, memory retention with optimal review can be simulated in the following graph:

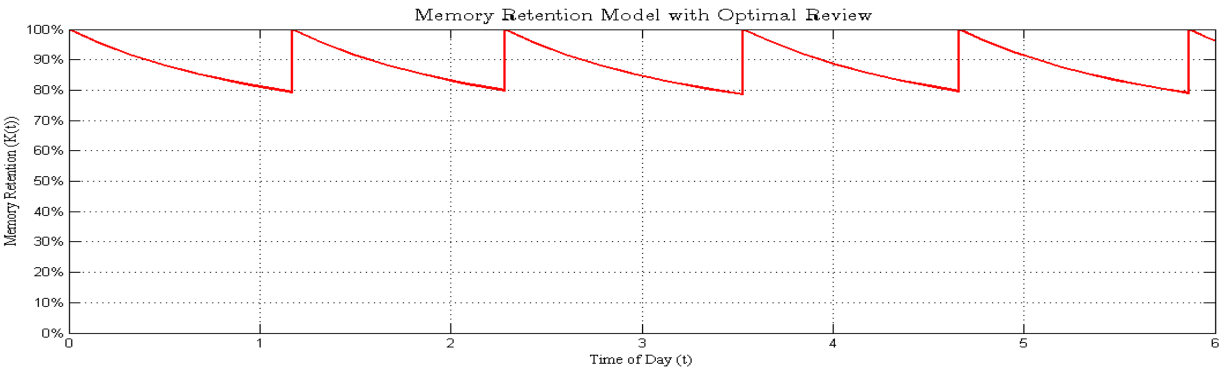

Figure 6. Memory Retention Graph with Optimal Reviews

Based on the three review strategies above, the simulation results indicate that learning without review causes memory retention to decline significantly and is difficult to maintain in the long term. The random review strategy provides a temporary increase in retention, but is unable to maintain consistent retention stability. Meanwhile, the optimal review strategy produces a stable and efficient retention pattern. Reviews are conducted just before a significant decline occurs, so that memory retention can be maintained in the long term with a more controlled number of repetitions. Thus, the optimal review strategy has proven to be the most effective compared to strategies without review or random review [11].

d) Benefits of an Optimal Review Strategy Compared to a Strategy Without Review or Random Review

Following are some advantages of the spaced repetition method with an optimal repetition strategy compared to a strategy without repetition or a random repetition strategy.

Table 4. Comparison of Memory Retention with Optimal Review, Random Review and without Review

Compare Aspects	Without Review	Random Review	Optimal Review
Interval Concept	None	Uncertain	Consistent And Planned
Time Efficiency	Very Low	Low	Very High
Retention Rate	Very Low	Low & Inconsistent	High and Stable
Forgetting Curve	Steep And Consistent Decline	Unpredictable Ups And Downs	Like A 'Staircase' That Is Becoming Flatter
Transfer To Long-Term Memory	None	Ineffective	Very Effective

IV. CONCLUSIONS AND RECOMMENDATIONS

Based on the results of the analysis and simulations that have been carried out, it can be concluded that the Learning and Forgetting model is a more realistic development than the basic Pure Forgetting model because it incorporates the learning or review process factor into the dynamics of memory retention [14]. The analytical solution of both models produces an exponential function that is capable of representing changes in memory retention levels over time. In the Learning and Forgetting model, the learning rate (α) and forgetting rate (λ) parameters have a significant effect on the shape of the retention curve and the steady-state value. A larger α value indicates a faster learning process, while a larger λ value accelerates the forgetting process. The interaction between these two parameters determines the level of memory retention in the long term.

In the context of determining the optimal review time, the model shows that there is a certain time when memory retention begins to decline beyond a predetermined threshold. Therefore, reviews should be conducted just before the decline in retention becomes more pronounced. This optimal review strategy has been proven to maintain memory retention at a stable level and prevent significant decline. A comparison of learning strategies shows that learning without review results in a retention curve that continues to decline to near zero. Meanwhile, a random review strategy yields better results than no review, but is less effective because the repetition time is not adjusted to the dynamics of memory forgetting. Thus, the optimal review strategy designed based on mathematical analysis of the model has been proven to be the most efficient in maintaining long-term memory retention and improving the effectiveness of the learning process [10], [11].

Based on the results of the research conducted, there are several recommendations for further research development. The learning and forgetting model used in this study still focuses on the internal dynamics of the learning and forgetting processes, so it does not fully represent the complex learning conditions in the real world. Therefore, future research should develop a model that incorporates external factors such as fatigue levels, learning motivation, and environmental distractions that can significantly affect a person's memory and memory retention stability. By considering these factors, it is hoped that the resulting model will be more comprehensive, realistic, and able to provide more accurate and adaptive review interval recommendations for individual conditions [12].

V. REFERENCES

[1] R. Musdalifah, "Pemrosesan Dan Penyimpanan Informasi Pada Otak Anak Dalam Belajar: Short Term And Long Term Memory," 2019.

[2] K. Yan, "Optimizing an English text reading recommendation model by integrating collaborative filtering algorithm and FastText classification method," *Heliyon*, vol. 10, no. 9, May 2024, doi: 10.1016/j.heliyon.2024.e30413.

[3] J. Kim, J. Park, T. A. Ulrich, and R. L. Boring, "A mathematical approach to using the forgetting curve to evaluate experience and training factors in human reliability analysis," *Ann Nucl Energy*, vol. 222, Nov. 2025, doi: 10.1016/j.anucene.2025.111591.

[4] S. A. Rhomadonah, M. R. Abdurrahman, M. D. Bokasa, I. Hidayat, M. Khoirunnisa, and A. Asmara, "Analisis Impostor Syndrome dalam Aspek Religiositas terhadap Waqf Behavior Mahasiswa IPB dengan Pendekatan Ebbinghaus Forgetting Curve," *AL-MUZARA'AH*, vol. 11, no. 2, pp. 187–199, Dec. 2023, doi: 10.29244/jam.11.2.187-199.

[5] K. Yao, J. Nguyen, and M. Mathur, "Spaced Repetition Learning in Radiology Education: Exploring Its Potential and Practical Application," *Journal of the American College of Radiology*, vol. 22, no. 1, pp. 15–21, Jan. 2025, doi: 10.1016/j.jacr.2024.11.020.

[6] J. M. J. Murre and J. Dros, "Replication and analysis of Ebbinghaus' forgetting curve," *PLoS One*, vol. 10, no. 7, Jul. 2015, doi: 10.1371/journal.pone.0120644.

[7] B. Tabibian, U. Upadhyay, A. De, A. Zarezade, B. Schölkopf, and M. Gomez-Rodriguez, "Enhancing human learning via spaced repetition optimization," *Proc Natl Acad Sci U S A*, vol. 116, no. 10, pp. 3988–3993, 2019, doi: 10.1073/pnas.1815156116.

[8] B. Settles and B. Meeder, "A Trainable Spaced Repetition Model for Language Learning." [Online]. Available: https://www.duolingo.com

[9] S. Reddy, I. Labutov, S. Banerjee, and T. Joachims, "Unbounded human learning: Optimal scheduling for spaced repetition," in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Association for Computing Machinery, Aug. 2016, pp. 1815–1824. doi: 10.1145/2939672.2939850

[10] J. Ye, J. Su, and Y. Cao, "A Stochastic Shortest Path Algorithm for Optimizing Spaced Repetition Scheduling," in *Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, Association for Computing Machinery, Aug. 2022, pp. 4381–4390. doi: 10.1145/3534678.3539081.

[11] J. Su, J. Ye, L. Nie, Y. Cao, and Y. Chen, "Optimizing Spaced Repetition Schedule by Capturing the Dynamics of Memory," *IEEE Trans Knowl Data Eng*, vol. 35, no. 10, pp. 10085–10097, Oct. 2023, doi: 10.1109/TKDE.2023.3251721.

[12] D. Kline, "Human-like Forgetting Curves in Deep Neural Networks," Jun. 2025, [Online]. Available: http://arxiv.org/abs/2506.12034

[13] B. Choffin, F. Popineau, Y. Bourda, and J.-J. Vie, "DAS3H: Modeling Student Learning and Forgetting for Optimally Scheduling Distributed Practice of Skills." [Online]. Available: https://mnemosyne-proj.org/

[14] K. Biedalak, M. Biedalak, F. Graliński, and J. Pokrywka, "Modeling Spaced Repetition with LSTMs," in *International Conference on Computer Supported Education, CSEDU - Proceedings*, Science and Technology Publications, Lda, 2023, pp. 88–95. doi: 10.5220/0011724000003470.

[15] B. Hermann Ebbinghaus, H. A. Ruger, and C. E. Bussenius, "MEMORY A CONTRIBUTION TO EXPERIMENTAL PSYCHOLOGY De subjecto vetustissimo novissimam promovemus scienttam" TRANSLATED BY PUBLISHED BY flfolkgr, Ctttmbte Ihmir rmti; NEW YORK CITY 1913."

[16] J. Peltokorpi and M. Y. Jaber, "Interference-adjusted power learning curve model with forgetting," *Int J Ind Ergon*, vol. 88, Mar. 2022, doi: 10.1016/j.ergon.2021.103257.

[17] Q. Xiao and J. Wang, "DRL-SRS: A Deep Reinforcement Learning Approach for Optimizing Spaced Repetition Scheduling," *Applied Sciences (Switzerland)*, vol. 14, no. 13, Jul. 2024, doi: 10.3390/app14135591.