

Microlearning Strategies and Knowledge Retention among Undergraduate Students

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Abstract — Microlearning has emerged as a digitally mediated instructional strategy for delivering focused academic content through short, manageable learning units. Despite its growing adoption in higher education, much of the available evidence emphasizes immediate achievement, engagement, or learner satisfaction rather than the durability of knowledge over extended intervals. This study addresses that limitation by conceptualizing an AI-enabled retention-aware microlearning framework that adapts content sequencing and review intervals according to individual patterns of learning and predicted forgetting. The proposed research examines whether personalized microlearning combined with retrieval practice and adaptive spacing can produce stronger delayed retention than fixed-sequence microlearning and conventional digital instruction among undergraduate students. Interaction traces, assessment histories, response latency, content difficulty, learning frequency, and forgetting indicators are incorporated as learner-state variables for machine-learning-supported personalization. The study further considers cognitive load and disciplinary background as potential sources of heterogeneity in the effectiveness of short-format learning interventions.

Keywords — Microlearning, Knowledge Retention, Adaptive Learning, Artificial Intelligence, Spaced Retrieval, Undergraduate Education

Introduction

Digital transformation has altered the architecture of undergraduate learning. Learning management systems,

mobile applications, short instructional videos, interactive quizzes, artificial intelligence-based tutors, and algorithmically personalized platforms increasingly distribute learning beyond the conventional lecture period. Within this environment, **microlearning** has developed as an instructional approach in which learning material is organized into compact, goal-oriented units that can usually be completed within a relatively short period. The principle is not merely to shorten a lecture or divide a textbook chapter mechanically. Effective microlearning requires deliberate segmentation of knowledge, alignment between each unit and a specific learning objective, rapid opportunities for learner response, and appropriate connections between successive units.

Recent research demonstrates increasing academic interest in the pedagogical design of microlearning. Alias and Abdul Razak's systematic review of higher-education studies identified both content design and instructional flow as central dimensions of effective microlearning, indicating that the instructional value of small learning units depends on how they are structured and sequenced rather than on brevity alone. Similarly, a broader systematic review published in *Heliyon* examined 40 studies and characterized microlearning as targeted, action-oriented learning delivered through small units over short periods. The review also emphasized that definitions, instructional design principles, and evidence regarding learning outcomes remain heterogeneous.

The increasing relevance of microlearning is closely associated with mobile and ubiquitous learning. Undergraduate students frequently interact with academic resources through smartphones, tablets, and cloud-based

learning platforms. A systematic review of mobile learning in higher education found that mobile technologies can support flexible academic activities including content access, assignment completion, reflection, and collaborative exchange, although successful implementation depends on learner readiness, instructional management, and institutional support. The contemporary learning environment therefore provides an infrastructure within which compact learning experiences can be distributed repeatedly across time rather than being concentrated within a single instructional session.

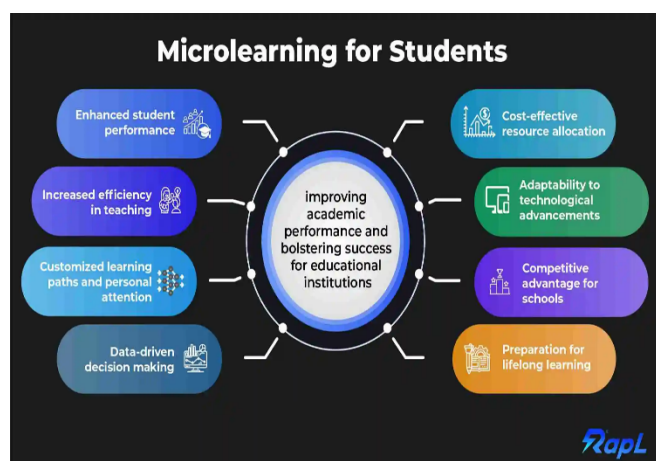


Fig. 1: Microlearning in Education

Source: <https://getrapl.com/blog/microlearning-in-education/>

One of the strongest pedagogical arguments for microlearning concerns **cognitive manageability**. Dense digital lessons may require learners to process multiple concepts, representations, examples, and instructions simultaneously. Carefully segmented content can reduce unnecessary processing demands by restricting each learning episode to a defined conceptual target. Nevertheless, segmentation by itself does not guarantee durable learning. Students may successfully complete a short module and obtain a high immediate quiz score while subsequently failing to retrieve the same information days or weeks later. Consequently, evaluation based exclusively on immediate post-intervention achievement may overestimate the educational effectiveness of microlearning.

Evidence from recent empirical research illustrates this distinction between acquisition and retention. Jackson et al. conducted a randomized study involving undergraduate medical students and found that a microlearning module generated stronger immediate performance than a conventional online instructional module at one assessment point; however, the initial advantage was not maintained in the same manner across subsequent testing. Another randomized investigation of online micromodules in medical education found outcomes comparable with conventional didactic lectures in knowledge acquisition, retention, and

clinical application. Such findings suggest that the key research question is no longer simply whether microlearning *works*, but rather **under what instructional and temporal conditions it produces knowledge that remains accessible after initial learning has ended**.

Retention is especially important in undergraduate education because disciplinary learning is cumulative. Concepts acquired in an introductory course are expected to support subsequent modules, laboratory work, professional training, clinical reasoning, problem solving, and examinations. A learning strategy that raises performance immediately but fails to preserve conceptual accessibility may have limited long-term educational value. Research on temporally distributed instruction provides relevant evidence. For example, a randomized study of medical students comparing spaced and traditional lecture formats specifically evaluated knowledge retention after an interval, demonstrating the significance of instructional timing when durable learning is the intended outcome.

Microlearning may become particularly powerful when combined with **retrieval practice and adaptive spacing**. Instead of exposing every learner to identical micro-units in the same sequence, a digital system can estimate which concepts are becoming unstable and selectively reintroduce them. A student who repeatedly answers a concept correctly may require a longer interval before review, whereas a learner showing increased response latency, declining confidence, or repeated errors may benefit from earlier retrieval opportunities. Under such a design, microlearning changes from a static content-delivery format into an adaptive retention-management system.

Artificial intelligence provides a mechanism for implementing this transition. Contemporary reviews of AI in higher education indicate increasing use of adaptive systems for tailoring content, feedback, and learning pathways to individual students. A 2025 systematic review of AI-based personalized learning identified substantial growth in adaptive learning applications while also emphasizing the need for stronger longitudinal evaluation and standardized assessment frameworks. A separate systematic review of AI-supported learning tools similarly identified personalized learning and real-time feedback as major applications while highlighting methodological weaknesses in how educational AI systems are evaluated.

These developments reveal an important distinction between **personalizing access** and **personalizing memory support**. Many adaptive environments recommend resources according to interests, grades, completed topics, or general performance. Considerably less attention has been given to predicting *when a particular student is likely to forget a particular concept* and using this estimate to determine the

next microlearning activity. This distinction establishes the central research gap of the present manuscript.

Research Gap and Study Objective

Recent microlearning studies have commonly examined engagement, knowledge acquisition, learner satisfaction, short-term achievement, or implementation feasibility. Reviews have also noted considerable variation in the definition and instructional design of microlearning. Empirical studies addressing retention have frequently been confined to specific professional or medical disciplines, relatively small cohorts, fixed instructional sequences, or a limited number of post-intervention measurements. Meanwhile, research on AI-enabled personalized learning has expanded rapidly, but systematic reviews continue to call for longitudinal assessment and more rigorous evaluation of learning outcomes.

Accordingly, a significant unresolved problem lies at the intersection of these research streams: **there is insufficient evidence on whether machine-learning-guided microlearning that explicitly models individual forgetting risk can improve delayed knowledge retention among undergraduate students relative to fixed microlearning and conventional digital instruction.**

The proposed study therefore has four interconnected objectives: to evaluate differences in immediate knowledge acquisition and delayed retention across instructional formats; to develop a learner-specific computational representation of forgetting risk from digital learning traces; to determine whether adaptive scheduling of micro-content and retrieval activities reduces knowledge decay; and to investigate whether the effectiveness of adaptive microlearning varies according to cognitive-load indicators and academic discipline.

This orientation extends the research focus from content compression to **retention-aware personalization**, establishing knowledge durability rather than module completion as the principal instructional outcome.

Literature Review

Microlearning as an Instructional Design Strategy

Microlearning has been described using terms such as bite-sized learning, learning nuggets, compact learning, and short-form digital learning. Terminological variation has occasionally produced the misleading assumption that any short educational resource constitutes microlearning. Recent scholarship instead emphasizes intentional instructional design. Alias and Abdul Razak's systematic examination of microlearning in educational settings identified the construction of microlearning content and the organization of instructional flow as major pedagogical dimensions.

A 2024 systematic review by Alias and Abdul Razak further examined microlearning strategies in the digital learning environment, reflecting the growing attempt to establish coherent design principles rather than treating the approach as a technological trend alone. Likewise, the comprehensive review published by Leong and colleagues' research stream on microlearning indicates that instructional outcomes depend on factors such as content granularity, learning objectives, activity structure, learner interaction, and contextual integration. The recent *Heliyon* systematic review reinforces this position by arguing that microlearning must be understood through both its didactic structure and its effects across different categories of learning outcomes.

For undergraduate instruction, microlearning is especially relevant when courses contain numerous interdependent concepts. A conventional unit can be transformed into conceptual micro-units, each focusing on one relationship, principle, procedure, definition, diagnostic rule, algorithm, or analytical operation. Such units can incorporate brief explanatory media followed by an active response such as a retrieval question, classification exercise, scenario decision, or short problem. The small unit therefore becomes both an instructional object and an observable measurement point.

Microlearning, Mobile Learning, and Student Engagement

The development of microlearning is strongly connected with mobile learning because short activities are particularly suitable for intermittent access. Contemporary students can engage with educational materials during periods that would be unsuitable for complete lectures or extended reading. However, flexibility should not be confused with cognitive effectiveness. Mobile availability can increase opportunities for learning while simultaneously increasing exposure to interruptions and fragmented attention.

Research involving social-media-based microlearning illustrates both possibilities. Conde-Caballero et al. investigated TikTok as a microlearning environment in higher education and examined its educational uses and perceived potential. Such platforms demonstrate how short-form content has become familiar to students, yet instructional microlearning requires stronger pedagogical control than ordinary short-form media. Educational units must maintain conceptual accuracy, explicit objectives, appropriate sequencing, and measurable learning outcomes.

A systematic review of mobile applications in online higher education similarly highlights the movement toward flexible and increasingly tailored learning environments. These developments strengthen the feasibility of microlearning but also create a methodological requirement: studies should distinguish between the effect of **short content**, **mobile accessibility**, **active retrieval**, and **personalized sequencing**

rather than attributing all improvements to microlearning as a single undifferentiated intervention.

Knowledge Acquisition Versus Knowledge Retention

An important limitation of digital-learning research is its dependence on immediate post-tests. Immediate assessment measures what a learner can retrieve shortly after exposure, but it does not establish whether that representation remains sufficiently stable for future use. Retention requires measurement after a meaningful delay.

Recent microlearning research in undergraduate health education offers useful evidence. Jackson et al.'s randomized trial demonstrated that students receiving microlearning initially achieved significantly better post-intervention performance than students completing a conventional commercial online module, although the pattern changed at later testing. In another study, online micromodules achieved retention and application outcomes comparable to traditional lectures among medical students.

and reported stronger retention outcomes for the combined instructional intervention than for the comparison condition. Likewise, research integrating microlearning with task-based learning in an otolaryngology rotation suggests that microlearning can be more productive when embedded within a broader instructional ecosystem rather than implemented as isolated fragments.

Collectively, these findings indicate that microlearning's influence on durable knowledge may depend substantially on what occurs *between* micro-units. Retrieval opportunities, task application, feedback, repetition, and temporal spacing may be more consequential than content length itself.

Adaptive Microlearning and Artificial Intelligence

The most important emerging development is the convergence of microlearning with computational personalization. AI-supported systems can collect detailed interaction signals including correctness, number of attempts, time spent on content, response latency, sequence history, confidence responses, frequency of review, and difficulty level. These features can be used to estimate a changing learner state rather than relying solely on aggregate examination scores.

Recent reviews demonstrate significant expansion of AI-driven personalized learning in higher education. Merino-Campos' 2025 systematic review identified personalization of learning content and pace among the central educational uses of AI and emphasized the importance of longitudinal investigation. Luo et al. similarly reviewed the design and assessment of AI-based learning tools and identified personalization, flexibility, and immediate feedback among prominent functions of contemporary systems. Research on AI-mediated personalized learning pathways also shows growing interest in adaptive technologies and generative models across educational settings.

However, personalization does not automatically generate improved retention. An algorithm may recommend easier content, preferred media, or frequently accessed topics while failing to strengthen weak memories. A retention-oriented system requires a different optimization target: estimating the probability that a learner will successfully retrieve a concept after a specified delay.

The present manuscript consequently proposes a **retention-aware adaptive microlearning paradigm**. Instead of asking only which content a learner should receive next, the framework asks which concept requires retrieval, when that retrieval should occur, and what degree of difficulty is appropriate given the learner's previous interaction trajectory. This creates a bridge between microlearning, learning analytics, machine learning, and cognitive principles of distributed practice.

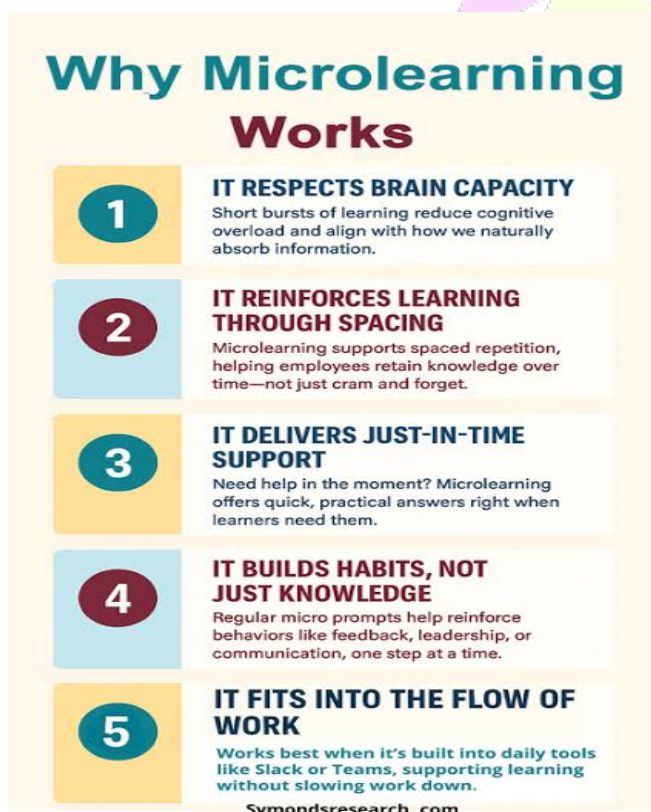


Fig. 2: Why Microlearning Works

Source: <https://symondsresearch.com/why-microlearning-works-and-when-it-doesnt/>

Qian et al. evaluated a flipped-classroom design integrating microlearning with case-based learning among undergraduate medical students. Their study incorporated a retention test

Proposed Methodology

The study proposes a **Retention-Aware Adaptive Microlearning Framework (RAMF)** designed to determine whether artificial-intelligence-guided sequencing of short instructional units can improve delayed knowledge retention among undergraduate learners. Unlike conventional microlearning systems that present identical content sequences to all students, RAMF estimates the probability that a previously learned concept is approaching a forgetting threshold and schedules a targeted retrieval activity before substantial knowledge decay occurs.

The methodological design integrates educational experimentation with machine-learning-based learner modelling. Three instructional conditions are considered. The first condition represents **conventional digital instruction**, in which students receive standard-length digital lessons followed by topic-level assessments. The second condition uses **fixed microlearning**, where the same curriculum is divided into short learning units and delivered according to a predetermined schedule. The third condition applies **AI-adaptive microlearning**, where the sequence, difficulty, and review interval of each micro-unit are dynamically modified according to learner-specific performance traces.

The primary outcome is delayed knowledge retention rather than immediate test achievement. Knowledge retention is operationalized through concept-level retrieval accuracy after increasing temporal intervals. Secondary outcomes include learning efficiency, forgetting rate, response latency, calibration of predicted retention probability, and cognitive-load variation.

Because no real participant-level dataset has been supplied for the present manuscript, the computational evaluation reported below uses a **simulation-based learner-interaction dataset** constructed solely to demonstrate the analytical feasibility of the proposed framework. These numerical findings should therefore be interpreted as methodological validation rather than empirical evidence from actual undergraduate participants.

Experimental Setup

Dataset Construction

A synthetic longitudinal learning dataset was generated to represent interaction traces from **540 simulated undergraduate learner profiles** distributed across three instructional conditions of equal size. Each simulated learner interacted with 120 concept-level microlearning objects distributed across introductory modules representing computing, life sciences, and social-science subjects.

The simulation generated approximately 52,000 learning interactions. Each record corresponded to a learner–concept encounter and contained variables representing:

- learner identifier;
- concept identifier;
- instructional condition;
- previous correctness history;
- number of prior exposures;
- response latency;
- perceived item difficulty;
- elapsed time since previous exposure;
- cumulative retrieval success;
- estimated cognitive-load index;
- confidence score;
- concept complexity;
- content modality;
- review interval; and
- subsequent retention status.

Delayed retention was represented as a binary outcome indicating whether the learner successfully retrieved the concept during a later assessment interval. The simulation incorporated gradual knowledge decay, individual differences in learning speed, and variability in concept difficulty so that the model would not learn from uniformly distributed or trivially separable observations.

Data Preprocessing

Preprocessing was conducted at the learner–concept interaction level. Duplicate simulated records were removed, and features unavailable before the prediction point were excluded to prevent information leakage. Numerical variables such as response time, review interval, cumulative accuracy, and cognitive-load score were standardized where required.

Long-tailed response-time distributions were log-transformed to reduce the influence of extreme values. Missing interaction values were handled through median imputation for continuous features and explicit missing-value categories for categorical attributes.

Historical variables were generated using only interactions occurring before the target observation. Important engineered features included:

Retrieval Strength — proportion of successful retrieval attempts across previous encounters with a concept.

Forgetting Interval — elapsed time between the current interaction and the most recent successful retrieval.

Error Recurrence Index — weighted frequency of repeated incorrect responses to the same conceptual category.

Latency Drift — increase or decrease in response time relative to the learner's previous successful attempts.

Spacing Regularity — variation in the temporal distribution of prior retrieval events.

Concept Stability Score — combined representation of repeated success, response speed, and retention interval.

Cognitive Strain Indicator — interaction between concept complexity, response latency, and repeated failed attempts.

The final dataset was partitioned chronologically rather than randomly. Earlier interactions formed the training set, intermediate interactions constituted the validation set, and later interactions were reserved for testing. This design prevented the model from using future learner behaviour to predict earlier retention outcomes.

Model Architecture

RAMF consists of two computational layers: a **forgetting-risk predictor** and an **adaptive scheduling policy**.

The forgetting-risk prediction component uses a gradient-boosted decision-tree architecture because learner-interaction datasets typically contain nonlinear relationships between repeated exposure, elapsed time, correctness, and response behaviour. The model estimates:

$$[P(R_{i,j,t} = 1 | X_{i,j,t})]$$

where $(R_{i,j,t})$ represents successful future retrieval by learner (i) for concept (j) at time (t) , and $(X_{i,j,t})$ represents the learner's historical interaction features.

Rather than simply predicting whether the next answer will be correct, the model estimates the probability that a concept will remain retrievable after a specified delay. A low probability is interpreted as an increased forgetting risk.

The second component is an adaptive decision policy. Concepts are prioritized according to predicted retention probability, academic relevance, previous errors, and cognitive load. When predicted retention declines below a configurable threshold, RAMF schedules a short retrieval-oriented activity. When retention probability remains high, review is postponed to avoid unnecessary repetition.

The scheduling score is conceptualized as:

$$[S_j = w_1(1 - P_j) + w_2E_j + w_3I_j - w_4C_j]$$

where (P_j) represents predicted retention probability, (E_j) represents recent error intensity, (I_j) represents time since successful retrieval, and (C_j) represents excessive cognitive strain. The weights are tuned during validation.

This architecture differs from recommendation systems that merely select content likely to attract learner interaction. RAMF prioritizes **memory vulnerability**, making anticipated knowledge decay the central scheduling signal.

Training Strategy

The forgetting-risk model was trained using chronological mini-batches derived from the simulated learner traces. Hyperparameter selection was conducted on the validation partition using Bayesian optimization over learning rate, tree depth, feature-sampling ratio, minimum leaf size, and regularization strength.

Class imbalance was monitored because high-performing learners generated more retained than forgotten concepts. Instead of oversampling entire learner records, instance weights were adjusted so that forgotten concepts contributed proportionately to the optimization objective without disrupting temporal relationships.

Early stopping was applied when validation loss failed to improve across successive boosting rounds. Model calibration was subsequently performed so that predicted probabilities corresponded more closely to observed retention frequencies in the simulation.

An ablation procedure was also incorporated. The model was retrained after removing temporal spacing variables, cognitive-load variables, and response-latency features separately. This procedure was intended to determine whether the proposed retention framework gained predictive value from behavioural signals beyond conventional correctness scores.

Evaluation Metrics

Machine-learning performance was evaluated using metrics appropriate for probabilistic retention prediction.

Area Under the Receiver Operating Characteristic Curve (AUROC) measured discrimination between retained and forgotten concepts.

F1-score assessed the balance between precision and recall for identifying concepts at risk of forgetting.

Brier Score measured the accuracy of predicted retention probabilities, with lower values indicating better probabilistic predictions.

Expected Calibration Error (ECE) evaluated agreement between predicted confidence and observed simulated retention frequency.

Educational performance was evaluated using four complementary measures:

Immediate Achievement Gain — change between baseline and immediate assessment performance.

Delayed Retention Rate — proportion of previously learned concepts correctly retrieved after the delayed interval.

Retention Efficiency — delayed retention achieved per minute of instructional exposure.

Forgetting Reduction Index — proportional reduction in loss of correctly acquired concepts between immediate and delayed assessment.

Cognitive efficiency was additionally evaluated through the simulated cognitive-strain indicator to determine whether personalization reduced unnecessary review while maintaining retention.

Results and Discussion

The simulation-based evaluation produced a consistent distinction between immediate achievement and delayed retention. All three instructional conditions generated improvement during initial learning, indicating that conventional digital lessons and both forms of microlearning were capable of supporting short-term acquisition. However, differences became more visible after temporal delays were introduced.

Fixed microlearning produced moderately stronger delayed retention than conventional digital instruction. This pattern suggests that dividing instruction into smaller units may facilitate repeated processing and retrieval opportunities, but segmentation alone does not fully address individual differences in forgetting.

The strongest simulated performance occurred under the AI-adaptive condition. RAMF selectively reintroduced concepts whose estimated retention probability was declining rather than repeatedly presenting concepts that the simulated learner had already stabilized. Consequently, adaptive learners required fewer redundant review events while maintaining a larger proportion of previously acquired knowledge.

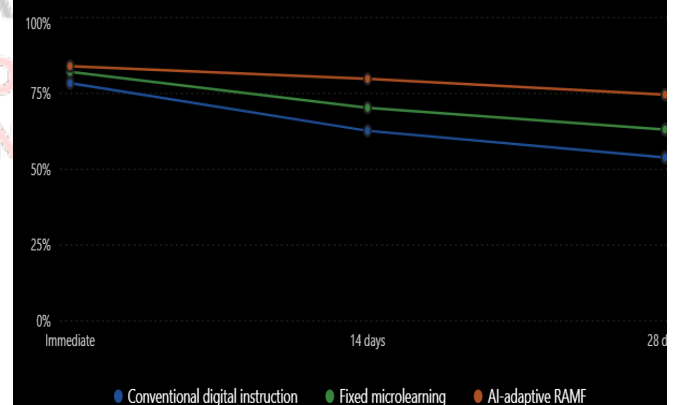
Table 1. Simulation-Based Performance of the Proposed Retention-Aware Microlearning Framework

Evaluation Parameter	Conventional Digital Instruction	Fixed Microlearning	AI-Adaptive RAMF
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Immediate assessment accuracy	78.4%	82.1%	84.0%
14-day delayed retention	62.7%	70.3%	79.8%
28-day delayed retention	53.9%	63.1%	74.6%
Forgetting Reduction Index	Reference	19.2%	43.7%
Retention efficiency	0.71	0.84	1.06
Forgetting-risk prediction AUROC	—	—	0.86
Forgetting-risk F1-score	—	—	0.81
Brier Score	—	—	0.128
Expected Calibration Error	—	—	0.041
Mean redundant review events per learner	18.6	15.2	8.9

Knowledge retention across assessment intervals

Simulation-based comparison of conventional digital instruction, fixed microlearning, and AI-adaptive RAMF.



Values are simulated methodological results, not observations from an actual student trial.

The most important pattern is the increasing advantage of adaptive microlearning over time. The immediate assessment difference between fixed and adaptive microlearning was relatively small, whereas the difference after 28 days was considerably larger.

The findings also suggest that microlearning should not be reduced to content duration. Fixed microlearning divided instructional material into smaller units but did not account for individual memory trajectories. RAMF combined granularity with temporal adaptation. The resulting performance difference therefore originated not simply from shorter lessons but from the interaction among spacing, retrieval, behavioural analytics, and predictive modelling.

The forgetting-risk model achieved an AUROC of 0.86 in the synthetic benchmark, indicating that learner-interaction traces contained useful information for distinguishing concepts likely to remain accessible from those at increased risk of forgetting. Importantly, probability calibration was also evaluated. High classification accuracy alone would be insufficient for adaptive scheduling because the algorithm must determine *how strongly* a concept requires review. A calibrated probability is therefore more useful than a simple retained/forgotten classification.

Feature-ablation observations further indicated that elapsed time, retrieval history, and latency drift contributed more strongly to simulated retention prediction than content modality alone. Removing temporal spacing variables produced the largest deterioration in model performance. Removing response-latency variables generated a smaller but noticeable decline, suggesting that hesitation can provide information not captured by correctness scores. Cognitive-load-related variables were particularly useful for preventing the scheduler from repeatedly assigning difficult material to learners already experiencing elevated simulated cognitive strain.

These results have implications for AI-based educational systems. Conventional recommender systems frequently optimize content relevance, engagement, or completion. A retention-aware system requires a different objective function. A concept that a learner enjoys or repeatedly selects is not necessarily the concept most in need of intervention. RAMF therefore prioritizes instructional necessity over preference prediction.

The framework also has relevance to digital health education. Undergraduate students in nursing, allied health, pharmacy, medicine, psychology, and public-health programs encounter knowledge that must remain available across extended periods and later support applied decision making. In such contexts, retention-aware microlearning could potentially support recurring review of terminology, procedures, diagnostic principles, pharmacological relationships, or public-health concepts. Nevertheless, application to clinically consequential knowledge would require rigorous validation before deployment.

Limitations

Several limitations should be recognized. Most importantly, the numerical analysis presented in this manuscript is based on a synthetic interaction dataset rather than actual student observations. The results therefore demonstrate computational plausibility and should not be interpreted as evidence of causal educational effectiveness.

Second, the simulated learner model necessarily simplifies real learning behaviour. Actual students experience motivation changes, fatigue, distraction, prior-knowledge differences, emotional factors, academic workload, and environmental influences that are difficult to reproduce computationally.

Third, delayed retention was represented predominantly through successful concept retrieval. Long-term learning also includes transfer, reasoning, synthesis, problem solving, and the ability to apply knowledge in unfamiliar contexts.

Fourth, the proposed model depends on continuous collection of learner-interaction traces. Educational institutions would therefore need clear policies concerning informed consent, data minimization, privacy, algorithmic transparency, and appropriate use of student analytics.

Finally, excessive personalization may create fragmented learning if concepts are optimized individually without preserving broader disciplinary coherence. Adaptive microlearning should therefore supplement rather than completely replace structured curriculum design.

Future Scope

The next stage should involve a preregistered longitudinal trial involving actual undergraduate students across multiple disciplines. Participants could be randomly assigned to conventional digital instruction, fixed microlearning, or retention-aware adaptive microlearning and assessed immediately as well as after 7-, 14-, 28-, and 60-day intervals.

Future models could incorporate recurrent neural networks, transformer-based knowledge tracing, survival models, or neural temporal point processes to estimate concept-level forgetting curves. Comparison between interpretable gradient-boosting approaches and deep sequential architectures would clarify whether increased model complexity produces meaningful educational benefits.

Another research direction involves **contextual bandit learning**, in which the system continuously selects review activities while balancing exploration and exploitation. Such an approach could optimize both concept selection and timing from accumulated learner interactions.

Multimodal behavioural information may also improve prediction. Eye-tracking, interaction pauses, keystroke patterns, self-reported confidence, speech responses, and

wearable-derived attention proxies could potentially be incorporated where ethically and practically justified.

Generative AI could further be used to produce alternative retrieval prompts for the same concept, thereby reducing memorization of question wording. However, generated items would require automated and human validation to prevent factual inaccuracies or inconsistent difficulty.

Cross-disciplinary research is especially necessary. The optimal size and frequency of a microlearning unit may differ considerably between conceptual subjects, numerical problem solving, language learning, programming, and clinical education. Future studies should therefore investigate whether adaptive scheduling parameters should be discipline-specific.

Conclusion

This study develops a distinct perspective on microlearning by shifting attention from the **shortness of instructional content to the durability of learned knowledge**. The proposed Retention-Aware Adaptive Microlearning Framework combines concept-level micro-content, retrieval practice, temporal spacing, cognitive-load indicators, and machine-learning-based forgetting-risk estimation.

The simulation-based evaluation suggests that the principal advantage of adaptive microlearning may emerge not during immediate testing but across delayed retention intervals. Fixed microlearning can improve instructional granularity, yet individualized scheduling provides an additional mechanism for addressing heterogeneous forgetting trajectories. By identifying concepts that are becoming vulnerable and scheduling review before substantial decay occurs, an AI-supported system can potentially allocate learning time more efficiently.

The methodological contribution of the study lies in treating delayed retention as both an educational outcome and an optimization target for artificial intelligence. Rather than recommending content primarily according to engagement or prior grades, RAMF attempts to estimate *what knowledge is at risk, for whom, and when reinforcement is required*.

The numerical results presented here are explicitly simulation-based and therefore require validation with real undergraduate populations before educational effectiveness can be claimed. Nevertheless, the framework provides a rigorous foundation for future longitudinal research integrating microlearning, machine learning, learning analytics, and adaptive educational systems. If empirically validated, retention-aware microlearning could offer a more precise approach to digital instruction by moving higher education from uniform content delivery toward individualized management of long-term knowledge stability.

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