

Determinants of Long-Term Learning Retention in Higher Education: A Systematic Review of Strategies and Challenges

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Abstract

This systematic review synthesises multidisciplinary research to evaluate the determinants of long-term Knowledge, Skills, Values, and Attitudes (KSVA) retention within higher education. By examining the synergy between cognitive learning theories and emerging technologies, the paper identifies evidence-based strategies such as spaced repetition, retrieval practice, and AI-driven adaptive learning as primary catalysts for enhancing knowledge durability and learner motivation. The analysis further investigates the interplay of cognitive load principles and technological mediation, noting that while adaptive instructional designs outperform traditional methods, their efficacy is often moderated by learner characteristics and digital access. Furthermore, the review identifies significant institutional barriers, including curriculum rigidity, resource disparities, and resistance to pedagogical reform, which impede the transition from short-term assessment-focused teaching to durable, retention-based models. The study concludes that optimizing long-term learning outcomes requires a holistic framework that integrates cognitive science, inclusive technological innovation, and supportive institutional policies.

Keywords

Engineering Education, Knowledge Sharing, Learning, Knowledge Retention, Skills Development, Higher Education, Educational Measurement

1. Introduction

Research on evidence-based instructional strategies and their impact on long-term retention of knowledge, skills, values, and attitudes (KSVA) has emerged as a critical area of inquiry due to the increasing demand for effective educational models that sustain durable learning outcomes. Over recent decades, the field has evolved from traditional lecture-based methods to incorporate cognitive theories and technological innovations, such as adaptive learning systems and AI-driven personalization, which aim to optimize retention and motivation (Nam & Nam, 2025; Mainul & Naznin, 2025; Alblowi, 2025). The practical significance of this research is underscored by the persistent challenge of knowledge decay, with studies demonstrating substantial declines in retention over months without reinforcement (Donker et al., 2022; Csaba et al., 2025). The integration of cognitive load theory and neuroplasticity insights has highlighted the importance of managing mental effort to enhance learning durability (Mesavila & Nóbrega, 2025 ; Baksi, 2025). These developments reflect a broader societal and institutional imperative to improve educational efficacy and learner preparedness in diverse contexts (Vaghela & Parsana, 2024; Manzura, 2025). Despite advances, a specific problem remains in understanding how cognitive and technological factors interact to influence the durability of KSVA retention across varying pedagogical and institutional frameworks. While evidence supports

strategies such as spaced repetition, retrieval practice, and adaptive pacing, gaps persist in comprehensively mapping their long-term effects across disciplines and learner populations (Lyle et al., 2020; Trumble et al., 2023; D., 2025). Conflicting perspectives exist regarding the relative efficacy of traditional versus technology-enhanced methods, with some studies emphasizing the superiority of active, student-centered approaches, while others caution against overreliance on digital tools without adequate pedagogical integration (Hu et al., 2025). The consequences of these gaps include suboptimal instructional designs and institutional resistance to adopting retention-focused teaching models, which may hinder sustained academic and professional competence (Roehe et al., 2024; Mainul & Naznin, 2025).

This review constructs a conceptual framework grounded in cognitive learning theory, evidence-based instructional strategies, and institutional influences on pedagogy. Key concepts include cognitive load management, adaptive learning technologies, and institutional barriers to long-term memory consolidation (Yeo, 2024; Diyal et al., 2025; 赵, 2025). The framework elucidates the dynamic interplay between learner cognition, technological mediation, and systemic factors, providing a foundation for evaluating retention-based teaching models. The purpose of this systematic review is to synthesize current evidence on the impact of evidence-based instructional strategies on long-term KSVA retention, examine the interaction of cognitive and technological factors affecting knowledge durability, and identify pedagogical and institutional barriers influencing retention outcomes. This review aims to bridge existing knowledge gaps by integrating multidisciplinary findings and offering insights to inform the design and implementation of effective retention-focused educational practices. A comprehensive literature search was conducted across multiple databases, including peer-reviewed empirical studies and theoretical analyses published between 2016 and 2025. Inclusion criteria emphasized studies addressing long-term retention, cognitive and technological interactions, and institutional frameworks. Analytical methods involved thematic synthesis and critical appraisal to organize findings into coherent categories aligned with the conceptual framework. The review is structured to first explore cognitive and technological influences on retention, followed by an examination of pedagogical and institutional barriers, concluding with implications for retention-based teaching models.

1.1 Statement of Purpose

The objective of this report is to examine the existing research on evidence-based instructional strategies impact on long-term KSVA retention, interaction of cognitive and technological factors on knowledge durability, pedagogical and institutional barriers to long-term memory, influence of institutional frameworks on retention-based teaching models in order to synthesize current understanding, identify gaps, and inform future educational practices. This review is important as it addresses the critical challenge of sustaining knowledge retention over time, which is essential for effective learning outcomes across disciplines. By exploring how cognitive processes and technological tools interact to enhance or hinder durable learning, alongside institutional and pedagogical constraints, the report aims to provide a comprehensive foundation for developing optimized instructional models that support long-term knowledge retention and application.

1.2 Objectives

- Evaluate the current knowledge on the effectiveness of evidence-based instructional strategies for long-term KSVA retention.
- Identification and synthesis of pedagogical and institutional barriers impeding long-term memory consolidation.
- Comparing the influence of institutional frameworks on the adoption and success of retention-based teaching models.

2 Methods

This study adopts a systematic literature review approach to investigate the determinants of long-term Knowledge, Skills, Values, and Attitudes (KSVA) retention in higher education, guided by the principles of the PRISMA Flow Diagram to ensure transparency, replicability, and methodological rigor in the identification, screening, and selection of relevant studies. In addition, a conceptual review mapping approach was employed to structure the research process into interconnected stages, including query transformation, literature identification, screening and filtering, and thematic analysis, thereby enhancing both procedural clarity and analytical depth. The initial research question was systematically decomposed into multiple targeted queries addressing instructional strategies, cognitive mechanisms, technological factors, and institutional frameworks influencing long-term retention. A comprehensive database search

using these queries yielded 606 initial records, which was further strengthened through citation chaining incorporating both backward (reference list screening) and forward (identification of citing studies) approaches resulting in an additional 159 studies and a total of 506 candidate papers. After applying predefined inclusion and exclusion criteria, 489 studies were deemed eligible for further analysis. A relevance ranking process was then applied to refine the pool, from which 39 highly relevant studies were selected for in-depth analysis based on alignment with research objectives, conceptual depth, and methodological contribution. The selected studies were analysed using a thematic synthesis approach across four key dimensions: instructional strategies, cognitive factors, technological influences, and institutional frameworks. To complement the procedural rigor of the PRISMA framework, the methodology was further represented through a conceptual map structured into four layers research construction, literature identification, screening and filtering, and analytical dimensions illustrating the systematic progression from broad inquiry to focused analysis. This integrated methodological approach combines structured search strategies, advanced retrieval techniques, rigorous screening, and multi-dimensional analysis to ensure a comprehensive and robust investigation into long-term KSVA retention in higher education.

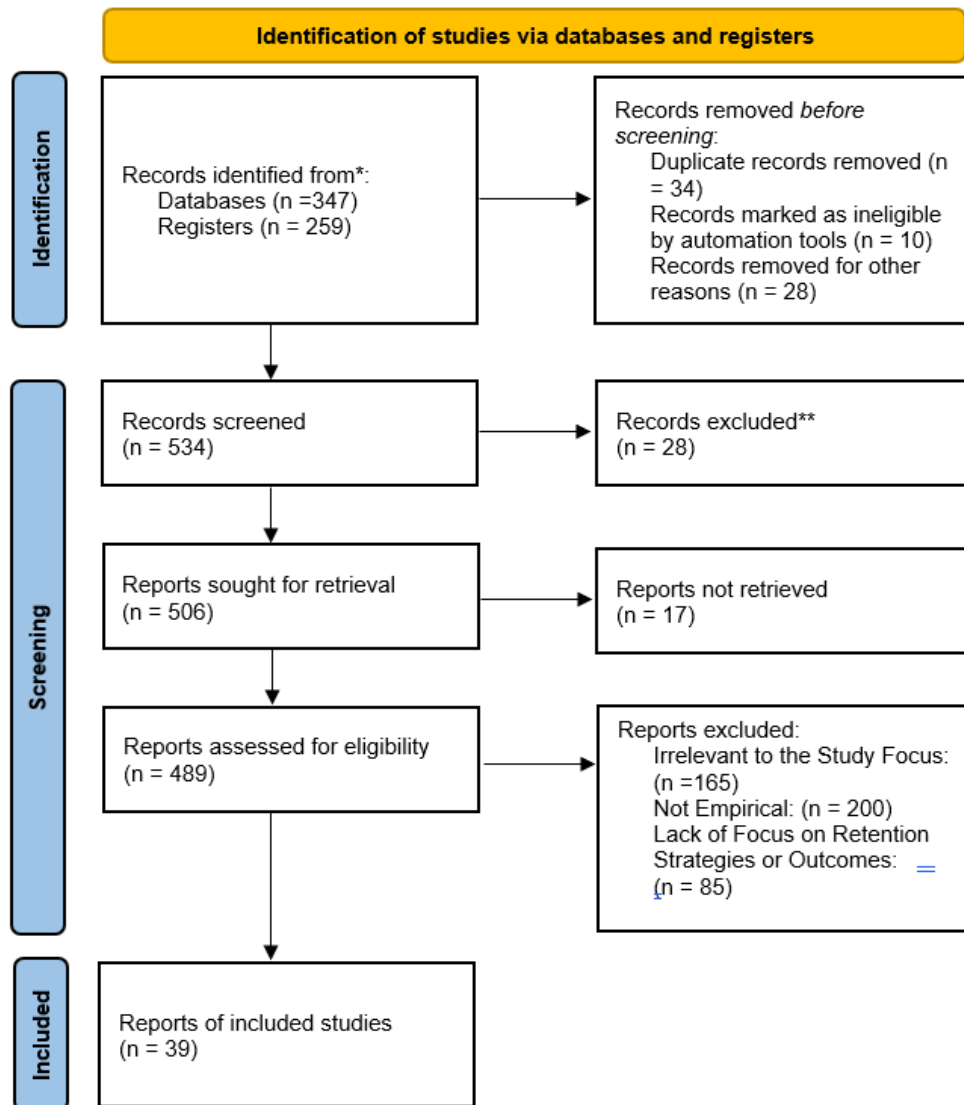


Figure 1. Flow diagram for methodology

3. Literature Review

Research on the determinants of long-term learning retention in higher education has gained significant momentum over the past decade, reflecting growing concern among educators and institutions about the sustainability of student learning outcomes beyond immediate assessment periods. This evolution has been driven by increasing recognition that traditional lecture-based models often fail to support durable learning, prompting educators and universities to critically reassess pedagogical approaches. As a result, higher education institutions have begun to prioritise evidence-based instructional strategies such as retrieval practice, spaced repetition, active learning, and cognitive load management to enhance retention. The systematic reviews and empirical studies have not only expanded theoretical understanding but have also placed pressure on universities to integrate learning science into curriculum design, teaching policy, and digital learning environments. Consequently, the field has emerged as a key area of educational research, bridging cognitive psychology and pedagogical practice and directly influencing institutional strategies to improve graduate competence and long-term academic success. The publication trend in Figure 1 demonstrates that long-term learning retention in higher education has evolved from a marginal topic into a rapidly emerging research field, particularly accelerating after 2020 due to increased digitalization and post-pandemic educational transformation.

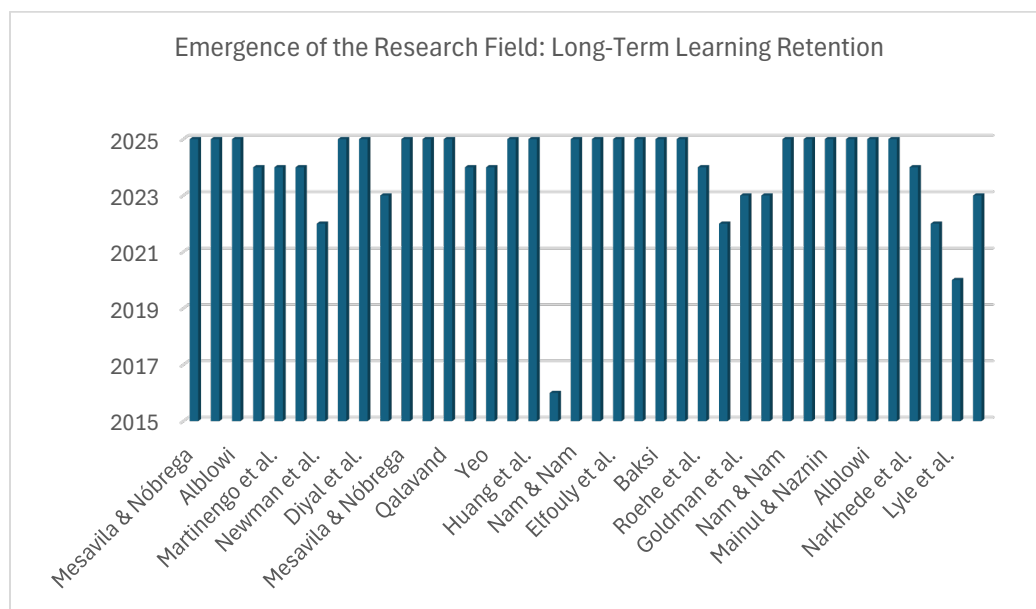


Figure 1. Emergence of the Research Field: Long-Term Learning Retention

3.1 Effectiveness of Evidence-Based Instructional Strategies for Long-Term KSVA Retention

A substantial body of research demonstrates that evidence-based instructional strategies significantly enhance long-term retention of knowledge, skills, values, and attitudes (KSVA). Approaches such as spaced repetition, retrieval practice, and active learning have consistently been associated with improved memory consolidation and transferability of knowledge across contexts. These strategies are grounded in cognitive science principles, particularly those relating to reinforcement, encoding variability, and retrieval strength. Spaced repetition, for instance, strengthens neural pathways through distributed exposure, while retrieval practice enhances recall efficiency by actively engaging memory reconstruction processes. Similarly, active learning strategies such as problem-based learning and peer instruction promote deeper cognitive processing, thereby improving not only retention but also the application of knowledge in real-world scenarios. Importantly, these strategies extend beyond cognitive gains to influence values and attitudes, fostering learner autonomy, motivation, and critical thinking (Mesavila & Nóbrega, 2025). However, the effectiveness of these strategies is often contingent upon contextual factors, including instructional design quality and learner characteristics, suggesting that their implementation must be carefully aligned with broader educational environments (Table 1).

Table 1. Institutional Influence & Learning Outcomes

Author(s)	Institutional Role	Learning Outcome
Mesavila & Nóbrega (2025)	Shapes instructional design	Student-centered learning
Mainul & Naznin (2025)	Policy influences adoption	Improved motivation
Alblowi (2025)	Determines access equity	Engagement ↑
Narkhede et al. (2024)	Supports evidence-based methods	Retention ↑
Martinengo et al. (2024)	Enables digital learning	Behaviour change
Ibragimov et al. (2024)	Resource allocation	Simulation success
Newman et al. (2022)	Infrastructure support	Tech effectiveness
LLandan (2025)	Professional development	Teacher effectiveness
Diyal et al. (2025)	Digital readiness	Learning persistence
Madan (2023)	Strategy implementation support	Retention & motivation ↑

3.2 Cognitive and Technological Interactions Influencing Knowledge Durability

The durability of learning is shaped by a dynamic interaction between cognitive processes and technological affordances. Cognitive theories highlight the importance of working memory limitations, cognitive load management, and schema construction in determining whether information is successfully transferred to long-term memory. Technological tools such as adaptive learning systems, simulation platforms, and intelligent tutoring systems play a critical role in mediating these cognitive processes. Personalising content delivery and pacing, these technologies can optimise cognitive load and enhance engagement. For example, adaptive systems dynamically adjust difficulty levels based on learner performance, thereby maintaining an optimal challenge point that supports sustained learning.

The integration of multiple external representations (MERs), including visual, symbolic, and interactive formats, has been shown to strengthen conceptual understanding and retention. These representations facilitate dual coding and reduce cognitive overload by distributing information processing across modalities. Despite these advantages, the effectiveness of technological interventions depends on their alignment with cognitive principles. Poorly designed digital tools may increase extraneous cognitive load, thereby hindering rather than supporting long-term retention (Table 2).

Table 2. Cognitive–Technological Interaction

Author(s)	Cognitive Mechanism	Technology Role
Mesavila & Nóbrega (2025)	Cognitive load management	Emotion + tech influence learning
Nam & Nam (2025)	Reinforcement learning models	AI improves knowledge durability
Qalavand (2025)	Cognitive scaffolding	Supports deep learning
Rohe et al. (2024)	Neuroscience-based learning	Enhances retention strategies
Yeo (2024)	Metacognition; cognitive load reduction	Improves transfer & retention
Diyal et al. (2025)	Multimedia learning: scaffolding	ICT enhances retention
Huang et al. (2025)	Motivation + cognitive load theory	Personalised apps improve learning
Gomes (2016)	Retrieval + adaptive feedback	Flashcard systems enhance recall

3.3 Pedagogical and Institutional Barriers to Long-Term Memory Consolidation

While evidence-based strategies and technological tools offer significant potential, their impact is often constrained by pedagogical and institutional barriers. Traditional lecture-based teaching models, which prioritise content coverage over deep learning, remain prevalent in many higher education contexts. These approaches often fail to engage learners in meaningful cognitive processing, limiting long-term retention. Institutional factors further exacerbate these challenges. Rigid curricula, high student-to-teacher ratios, and assessment systems focused on short-term performance, such as the high-stakes examinations, discourage the adoption of retention-oriented teaching practices. Additionally, limited access to resources and insufficient training in evidence-based pedagogy hinder educators' ability to implement innovative instructional strategies effectively. These barriers highlight a systemic misalignment

between educational objectives and instructional practices, suggesting that improving long-term retention requires not only pedagogical reform but also institutional transformation.

Table 3. Barriers to Long-Term Retention

Author(s)	Key Barriers
Nam & Nam (2025)	AI instability; convergence issues
Mesavila & Nóbrega (2025)	Ethical; motivational challenges
Elfouly et al. (2025)	Distraction; delayed feedback
Mainul & Naznin (2025)	Resource inequality; resistance
Baksi (2025)	Cognitive overload
Alblowi (2025)	Access disparities; integration issues
Roehe et al. (2024)	Surface learning; workload pressure
Donker et al. (2022)	Exam design limitations
Goldman et al. (2023)	Burnout; time constraints
Fraundorf et al. (2023)	Feedback timing; sequencing complexity

Pedagogical and institutional barriers further complicate the adoption of retention-focused strategies. The literature stated in Table 3 identifies systemic challenges such as resistance to innovation, unequal resource distribution, and reliance on traditional teaching methods, all of which impede the effective implementation of evidence-based practices (Mainul & Naznin, 2025; Vaghela & Parsana, 2024). While professional development and institutional support are recognized as critical enablers, there remains a lack of empirical research examining how institutional frameworks concretely influence long-term retention practices. Much of the existing work is theoretical or anecdotal, with insufficient evaluation of policy impacts, organizational culture, curriculum rigidity, and assessment constraints (Mainul & Naznin, 2025; Vaghela & Parsana, 2024; Roehe et al., 2024; Zhao, 2025).

3.4 Influence of Institutional Frameworks on Retention-Based Teaching Models

Institutional frameworks play a decisive role in shaping the adoption and success of retention-based teaching models. Policies related to curriculum design, assessment practices, and professional development directly influence how teaching and learning are structured within educational institutions. Institutions that prioritise learner-centred approaches and continuous assessment are more likely to support the integration of evidence-based strategies. For example, formative assessment practices encourage ongoing feedback and reflection, which are essential for long-term retention. Similarly, institutional support for professional development enables educators to acquire the skills needed to implement innovative teaching methods. Conversely, institutions that emphasise standardisation and summative assessment often create environments that are not conducive to retention-focused learning. In such contexts, educators may be constrained by time pressures and accountability measures that prioritise short-term outcomes over sustained learning. Thus, the effectiveness of retention-based teaching models is not solely determined by instructional design but is deeply embedded within broader institutional ecosystems.

In terms of cognitive and technological integration, advanced AI-driven adaptive pedagogies have shown strong potential in personalizing learning experiences by modeling learner engagement and optimizing retention outcomes (Nam & Nam, 2025; Zhao, 2025). The integration of cognitive theories such as Cognitive Load Theory and neuroplasticity into technology-enhanced platforms supports effective scaffolding and metacognitive regulation (Mesavila & Nóbrega, 2025; Baksi, 2025; Diyal et al., 2025). Nevertheless, the complexity of these interactions remains underexplored, with limited theoretical frameworks addressing variations across learner profiles. Additionally, some technological interventions risk cognitive overload and often fail to adequately incorporate motivational and emotional dimensions of learning, while issues of access inequality and digital literacy continue to hinder equitable implementation (Mesavila & Nóbrega, 2025; Diyal et al., 2025; Mainul & Naznin, 2025; Alblowi, 2025). Moreover, institutional frameworks play a role in shaping retention-based models, particularly through policies that support digital and adaptive learning environments. Some studies report improved clinical behavior and skill retention when such frameworks are effectively implemented, especially in health professions education (Martinengo et al., 2024; Elfouly et al., 2025). However, these influences are often context-specific and underreported, limiting their transferability. The interaction between institutional culture and instructional innovation, as well as issues of

scalability, sustainability, and equity, requires further investigation (Mainul & Naznin, 2025; Roche et al., 2024; Alblowi, 2025).

3.5 Adaptive Instructional Designs Integrating AI and Cognitive Load Principles

Recent advancements in artificial intelligence (AI) have enabled the development of adaptive instructional designs that integrate cognitive load theory to enhance learner engagement and retention. AI-driven systems can analyse learner behaviour in real time, enabling personalised learning pathways that adjust content complexity, pacing, and feedback mechanisms. These systems are particularly effective in managing cognitive load, as they can minimise extraneous load while optimising germane load to support schema construction. AI can sequence instructional materials to progressively build on prior knowledge, reducing cognitive overload and enhancing retention. Moreover, adaptive systems support sustained engagement by incorporating interactive and immersive learning experiences, such as simulations and gamified environments. These approaches not only improve knowledge retention but also influence learners' attitudes and motivation, contributing to holistic KSVA development.

Comparatively, adaptive instructional approaches are generally shown to outperform traditional methods in sustaining engagement and retention through personalized content delivery, real-time feedback, and scaffolded learning (Nam & Nam, 2025; Alblowi, 2025; Ibragimov et al., 2024). Hybrid models that combine adaptive and traditional techniques also demonstrate promise across diverse educational contexts ("Modern approaches to teaching methods...", 2024). Despite these advantages, challenges persist, including limited access to adaptive technologies in low-resource settings, difficulties integrating such systems into existing curricula, and inconsistent findings regarding the optimal level of personalization required (Alblowi, 2025; Ibragimov et al., 2024; Hu et al., 2025; Lyle et al., 2020).

The integration of artificial intelligence with cognitive load principles represents a further advancement in instructional design, with AI-driven frameworks demonstrating high predictive accuracy for learner retention and engagement through dynamic pacing and adaptive support (Nam & Nam, 2025; Zhao, 2025; Qalavand, 2025). Nonetheless, practical implementation is often hindered by insufficient instructor training and infrastructural limitations. Concerns also remain regarding the balance between automation and human facilitation, as well as ethical considerations related to data privacy and the potential over-reliance on AI (Diyal et al., 2025; Zhao, 2025). However, implementing AI-driven instructional design raises important considerations, including accessibility, data privacy, and the need for educator training. Additionally, the effectiveness of these systems depends on their alignment with pedagogical principles, underscoring the importance of integrating technological innovation with sound educational theory.

Table 4. Instructional Strategies & Retention Outcomes

Author(s)	Strategy	Retention Outcome
Nam & Nam (2025)	AI-adaptive learning	High retention; improved mastery
Elfouly et al. (2025)	Intermittent instruction	Significant mastery gains
Mainul & Naznin (2025)	Active & differentiated learning	Improved retention & motivation
Baksi (2025)	Spaced repetition; Active recall	Strong long-term retention
Alblowi (2025)	Adaptive learning systems	Higher retention vs traditional
Diyal et al. (2025)	Microlearning	Improved retention & flexibility
Narkhede et al. (2024)	Spaced + evidence-based learning	Enhanced retention
Donker et al. (2022)	Retrieval practice	Reduced knowledge loss
Lyle et al. (2020)	Spacing + retrieval	Long-term retention ↑
Trumble et al. (2023)	Distributed practice	Improved academic performance

The literature in Table 4 indicates that long-term KSVA retention is influenced by a complex interplay of instructional, cognitive, technological, and institutional factors. Evidence-based instructional strategies provide a strong foundation for enhancing retention, but their effectiveness is mediated by cognitive processes and technological design. At the same time, pedagogical and institutional barriers can significantly limit their impact, highlighting the need for systemic change. Emerging adaptive instructional models, particularly those leveraging AI, offer promising avenues for

addressing these challenges by aligning learning experiences with cognitive principles and individual learner needs. However, their success depends on supportive institutional frameworks and informed pedagogical implementation.

Across the reviewed studies, instructional strategies such as spaced repetition, retrieval practice, and adaptive learning consistently demonstrate strong effects on long-term retention. These strategies are underpinned by cognitive mechanisms including cognitive load management and metacognitive regulation, often enhanced through technological integration. However, barriers such as institutional resistance, cognitive overload, and technological limitations persist, highlighting the critical role of institutional frameworks in enabling effective implementation and sustained learning outcomes. The literature on long-term learning retention in higher education highlights several interconnected strengths and weaknesses across instructional, cognitive, technological, and institutional dimensions. Firstly, evidence-based instructional strategies such as spaced repetition, retrieval practice, and adaptive learning systems have consistently demonstrated significant improvements in long-term retention, learner motivation, and knowledge durability (Nam & Nam, 2025; Alblowi, 2025; Narkhede et al., 2024; Trumble et al., 2023). The incorporation of active learning approaches and cognitive load management further enhances meaningful knowledge consolidation (Mesavila & Nóbrega, 2025; Mainul & Naznin, 2025). However, these findings are often constrained by methodological limitations, including small sample sizes, short-term interventions, lack of control groups, and insufficient longitudinal follow-up, which limit generalizability and the ability to confirm sustained retention over time (Donker et al., 2022; Csaba et al., 2025; Roehe et al., 2024).

Finally, while systematic reviews and meta-analyses provide moderate to high-quality evidence supporting strategies such as distributed and retrieval practice (Trumble et al., 2023), methodological inconsistencies across studies continue to pose significant challenges. Variations in outcome measures, retention intervals, and learner populations complicate synthesis and meta-analytic conclusions (Roehe et al., 2024; Csaba et al., 2025). Many studies lack standardized assessment tools and fail to adequately control for confounding variables such as prior knowledge and motivation (Donker et al., 2022). Consequently, there is a critical need for more rigorous, longitudinal, and multi-institutional research to strengthen the evidence base and refine instructional models for long-term learning retention.

4. Results and Discussion

The results of this review indicate that evidence-based instructional strategies such as spaced repetition, retrieval practice, interleaved learning, and dual coding are highly effective in promoting long-term KSVA retention, particularly when they are intentionally aligned with cognitive science principles and supported by appropriate technological tools. These strategies enhance memory consolidation, improve recall accuracy, and foster deeper learning, although their effectiveness varies depending on contextual factors such as discipline, learner characteristics, and instructional design quality. At the same time, the findings reveal significant pedagogical and institutional barriers that impede long-term memory consolidation, including the dominance of traditional lecture-based teaching, limited educator training in memory-focused methods, time constraints within curricula, and assessment systems that prioritize short-term performance over durable learning. Institutional challenges such as a lack of policy support, insufficient technological infrastructure, and resistance to change further restrict the adoption of retention-based teaching models. Comparative analysis shows that institutional frameworks play a critical role in shaping the success of these models, with flexible, learner-centred institutions that promote continuous assessment, digital integration, and professional development achieving better outcomes than rigid, exam-oriented systems. The synthesis also highlights key research gaps, including limited longitudinal studies on retention, a lack of standardized KSVA measurement frameworks, and insufficient integration of cognitive and emerging technological approaches. Overall, the discussion demonstrates that improving long-term knowledge retention requires a holistic, system-level approach that aligns instructional strategies, cognitive processes, technological tools, and institutional policies to create sustainable and effective learning environments.

6. Conclusion

Evidence strongly shows that instructional strategies like spaced repetition, retrieval practice, active learning, and adaptive learning significantly improve long-term retention of knowledge, skills, values, and attitudes. These approaches enhance learning by managing cognitive load, promoting deeper understanding, and maintaining learner motivation. Technology, especially AI-driven adaptive systems and microlearning further strengthens retention by personalizing learning and aligning with how the brain processes and stores information. However, the effectiveness of these strategies depends on careful design, as challenges such as cognitive overload, timing of feedback, motivation, and unequal access to technology can limit outcomes. Institutional barriers including resistance to change, rigid

curricula, and lack of teacher training also hinder widespread adoption. While adaptive learning generally outperforms traditional methods, gaps remain in long-term and large-scale research. Moving forward, improving retention in education requires integrated approaches that combine cognitive science, technology, and strong institutional support, while also addressing issues of equity and access.

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