



MICROLEARNING AND SELF-REGULATED LEARNING IN HIGHER EDUCATION STUDENTS: A SYSTEMATIC LITERATURE REVIEW

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ABSTRACT

Microlearning delivers content in short, focused, and accessible units and has expanded rapidly in higher education, yet its relationship with students' self-regulated learning (SRL) has not been systematically mapped. This study charts microlearning design features and their influence on SRL through a systematic literature review following the PRISMA 2020 framework. Scopus was searched using terms for microlearning, SRL-related constructs, and higher education, restricted to English-language, open-access records published after 2014. The search returned 63 records; after abstract-level screening and eligibility assessment, 49 studies were included in the narrative synthesis. Engagement (36 studies) and motivation (21 studies) were the most frequently reported SRL constructs, while generative AI (10 studies), mobile applications (7 studies), and gamification (7 studies) were the most common delivery modalities. Four mechanisms emerged: reduced cognitive load, spaced repetition, content personalization, and greater flexibility over the learning process. Self-regulation and metacognition were rarely measured directly. These findings provide a roadmap for designing microlearning interventions that more deliberately strengthen students' capacity to regulate their own learning.

Keywords: *microlearning; self-regulated learning; higher education; systematic literature review; PRISMA*

INTRODUCTION

Digital transformation in higher education has pushed a shift away from conventional, one-size-fits-all instruction toward learning that is more flexible, modular, and learner-centered. One approach that has grown especially fast over the past decade is microlearning: delivering content in short, focused, easy-to-access units designed to fit how today's learners actually pay attention and how little uninterrupted time they often have (Taylor & Hung, 2022). Much of this growth traces back to mobile technology, short-form video platforms, and, most recently, the integration of generative AI into how learning content gets built (Lan & Zhou, 2025).

At the same time, self-regulated learning (SRL), a learner's ability to plan, monitor, and evaluate their own learning, has long been recognized as a strong predictor of academic success, particularly in online and blended settings that demand more independence from students (Xu et al., 2023; Cheng et al., 2023). The more flexibility students get over when and how they study, which is exactly what microlearning offers, the more their capacity for self-regulation matters for keeping that learning consistent and effective (Guo, 2022).

Although microlearning and SRL have each attracted a fair amount of review-level attention on their own, a systematic map of how the two specifically intersect in higher

education is still missing. Existing reviews tend to look at one or the other: some examine microlearning's effectiveness broadly across sectors, including corporate and health-professional training, without zeroing in on SRL mechanisms (Taylor & Hung, 2022; Monib et al., 2024); others examine SRL in online learning generally without highlighting microlearning's specific role as an intervention (Xu et al., 2023; Bergdahl et al., 2024). That gap is what motivates the present review: a systematic mapping of exactly where these two constructs meet, specifically for higher-education students.

Building on this background, the problem this review addresses is straightforward: there is no up-to-date (2015-2026), systematic map of how microlearning is designed and delivered in higher education, or of how it relates to specific SRL constructs. Without that map, it is difficult for instructional designers and researchers to identify patterns, gaps, and productive directions for microlearning that deliberately strengthens student learning autonomy, rather than assuming it happens automatically.

Research Questions

To address this problem, the review was designed around two research questions:

RQ1: What design characteristics and delivery modalities (format, platform, structure) characterize microlearning interventions implemented in higher education between 2015 and 2026, as reported in the open-access Scopus literature reviewed?

RQ2: To what extent, and through what mechanisms, does microlearning influence self-regulated learning components, including motivation, engagement, self-efficacy, autonomy/self-directed learning, and metacognition, among higher education students?

Objectives and Contribution

This study aims to (1) map the design characteristics and delivery-modality trends of microlearning in higher education based on the open-access Scopus corpus; (2) synthesize empirical evidence on how microlearning affects SRL constructs and the mechanisms behind that influence; and (3) identify research gaps that can guide future work and practice. Its main contribution is a research map that explicitly connects microlearning design characteristics to specific SRL constructs, an intersection that prior reviews have not mapped systematically, along with a conceptual synthesis framework explaining the mechanisms involved.

METHOD

Search Strategy and Screening Process

This review follows a systematic literature review (SLR) approach structured around the PRISMA 2020 reporting guideline (Page et al., 2021). We searched a single database, Scopus, using a Title-Abstract-KeyWord query that combined three term groups: (1) microlearning and its synonyms (micro-learning, bite-sized learning, learning nugget, micro-content, just-in-time learning, and similar terms); (2) self-regulated learning constructs (self-regulated learning, self-regulation, learner autonomy, self-directed learning, metacognition, motivation, engagement, learning strategies, student agency); and (3) the higher-education context (higher education, university, college, undergraduate, postgraduate). The search was



restricted to English-language, open-access documents published after 2014, returning 63 records.

Eligibility was determined using a PICOS framework adapted for an educational, non-clinical review context. Eligible studies needed to involve higher-education students (undergraduate, postgraduate, or degree-track learners) as the primary population; to treat microlearning, or a closely related construct such as bite-sized or just-in-time learning, as the actual pedagogical intervention or design focus rather than a peripheral mention; and to report an outcome tied to at least one SRL-related construct, such as motivation, engagement, self-efficacy, autonomy, or metacognition. No comparator condition was required, so both controlled and non-controlled designs were eligible, and eligible publication types included journal articles, conference papers, review articles, and short research notes.

Title-abstract screening and eligibility assessment followed the PICOS criteria outlined above, with particular attention to population relevance, the centrality of microlearning as the intervention under study, and a reported link to SRL constructs. This process excluded 14 records (for population mismatch, construct mismatch, or study-type mismatch), leaving 49 studies for narrative synthesis and thematic mapping. Figure 1 summarizes this selection process following the PRISMA 2020 format.

For full transparency and reproducibility, the complete Scopus search string (Title-Abstract-Keyword field) is reproduced below verbatim:

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TITLE-ABS-KEY ( ( microlearning OR "micro-learning" OR "micro learning" OR
"bite-sized learning" OR "short-form learning" OR "learning nugget*" OR "micro-
content" OR "micro lesson*" OR "micro module*" OR "just-in-time learning" ) AND (
"self-regulated learning" OR SRL OR "self-regulation" OR "learner autonomy" OR
"autonomous learning" OR "self-directed learning" OR metacognition OR motivation
OR engagement OR "learning strategies" OR "student agency" ) AND ( "higher
education" OR universit* OR college* OR undergraduate* OR postgraduate* OR
"university student*" OR "college student*" ) ) AND PUBYEAR > 2014 AND (
LIMIT-TO ( LANGUAGE , "English" ) ) AND ( LIMIT-TO ( OA , "all" ) )
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The query is structured around three concept blocks joined by the Boolean operator AND, with each block internally expanded using OR to capture relevant synonyms and wildcard variants (denoted by an asterisk). The first block captures microlearning and closely related terms describing short-form, modular instructional content, such as bite-sized learning, micro-content, and just-in-time learning. The second block captures self-regulated learning and its constituent constructs, including motivation, engagement, metacognition, and learner autonomy, reflecting the multidimensional nature of SRL as conceptualized in the literature. The third block restricts the population to the higher-education context through terms such as university, college, undergraduate, and postgraduate. Two field-level filters were applied directly within Scopus in addition to the publication-year restriction embedded in the query itself: publication language (English) and open-access status (all open-access categories). This three-block structure was designed to jointly capture only those records in which microlearning, an SRL-related construct, and the higher-education context are all explicitly present, rather than records that merely mention one of these elements in isolation.

Figure 1 presents the complete selection pathway using the PRISMA 2020 flow-diagram format, distinguishing the identification, screening, eligibility, and inclusion phases and reporting the exact record counts and exclusion reasons at each stage. This visual summary is intended to complement, rather than replace, the more detailed exclusion log and phase-by-phase narrative provided in the accompanying PRISMA Process Report.

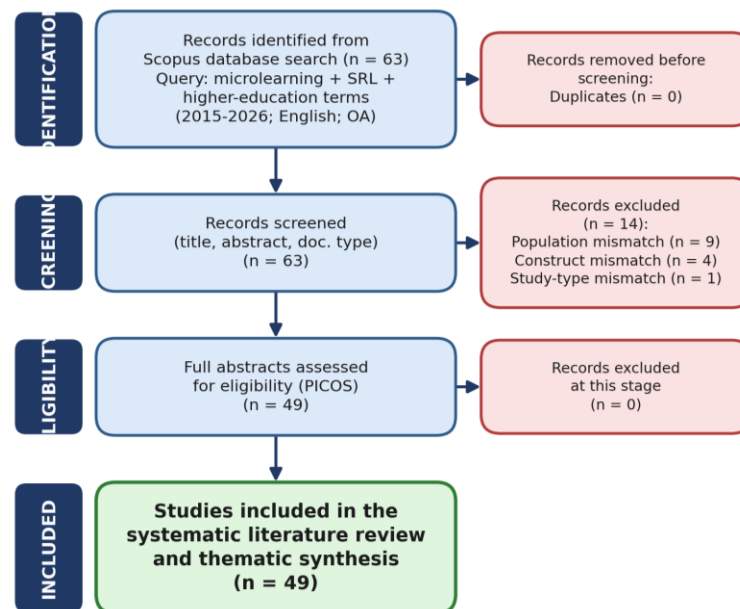


Figure 1: PRISMA 2020 Flow Diagram of the Study Selection Process ($n = 63 \rightarrow n = 49$)

Each included study was then coded along three non-exclusive dimensions: microlearning delivery modality/technology, the SRL construct(s) measured or discussed, and research design, using a keyword-assisted content-analysis protocol that was manually validated on borderline cases. The full search protocol, eligibility criteria, per-study exclusion log, complete list of included studies, and methodological considerations are documented separately in the accompanying PRISMA Process Report, given the extent of that documentation. A summary of the review's methodological scope and limitations is provided under Limitations below.

RESULTS AND DISCUSSION

General Characteristics of Included Studies

Of the 49 included studies, the majority were journal articles (39 studies; 79.6%), followed by conference papers (8 studies; 16.3%) and review articles (2 studies; 4.1%). Table 1 summarizes the general characteristics of the included studies.

**Table 1: General Characteristics of Included Studies (n = 49)**

Characteristic	Category	n	%
Document type	Journal article	39	79.6%
	Conference paper	8	16.3%
	Review article	2	4.1%
Publication period	2017	1	2.0%
	2021-2023	11	22.4%
	2024-2026	37	75.5%
Research design (non-exclusive)	Experimental / quasi-experimental	20	40.8% *
	Survey / correlational	19	38.8% *
	Qualitative	10	20.4% *
	Systematic review / conceptual framework	5	10.2% *

** Research-design percentages are calculated against the total of 49 studies; the sum exceeds 100% because several studies employed more than one design (e.g., mixed methods).*

The publication-year distribution shows a sharp growth trend: three-quarters of the included studies (75.5%) were published in just the last three years (2024-2026), confirming that the intersection of microlearning and SRL is a fast-growing and relatively young field within the higher-education literature (Figure 2). In terms of research design, experimental/quasi-experimental (20 studies) and survey/correlational (19 studies) approaches dominate the corpus, indicating that most included studies aimed to establish a causal or correlational relationship between microlearning and SRL outcomes rather than simply describing them (Figure 3).

Annual Publication Trend of Included Studies (n = 49)

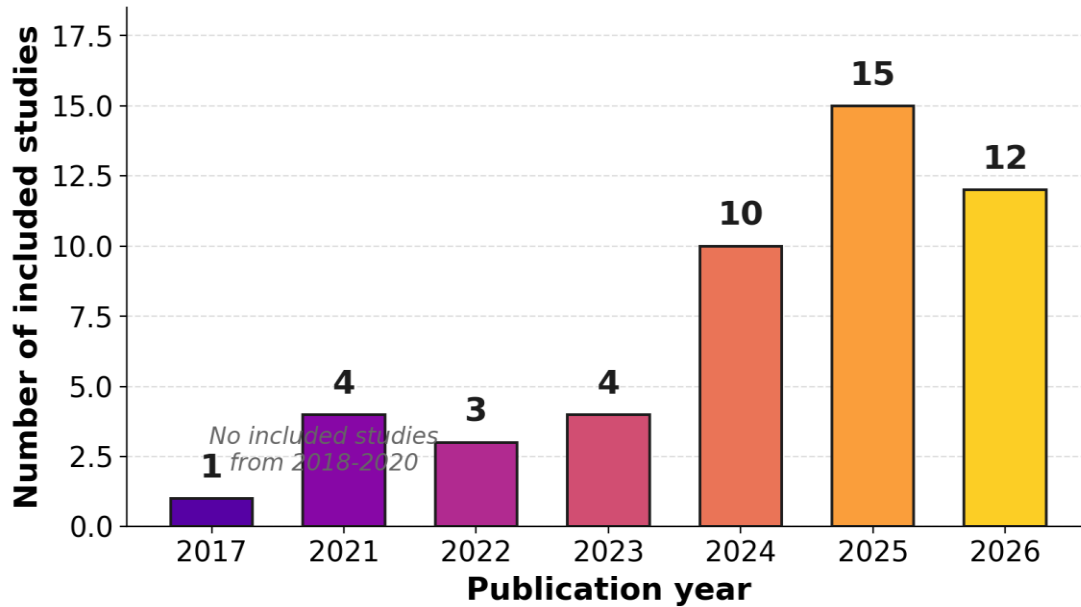


Figure 2: Annual Publication Trend of Included Studies (n = 49)

Distribution of Research Designs Among Included Studies (n = 49)

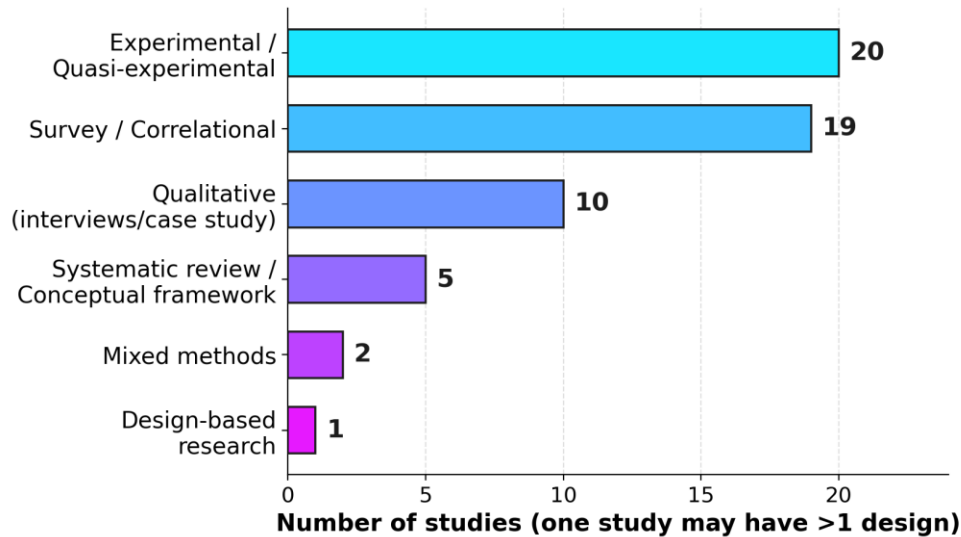


Figure 3: Distribution of Research Designs Among Included Studies

Research Map and Thematic Clustering

To visualize how microlearning delivery modalities relate to the SRL constructs measured, we mapped the co-occurrence of these two dimensions across the 49 included studies based on the thematic coding described under Method. Figure 4 presents this research map as a bubble diagram, where bubble size and color represent how often a given modality-construct combination appeared together in the corpus.

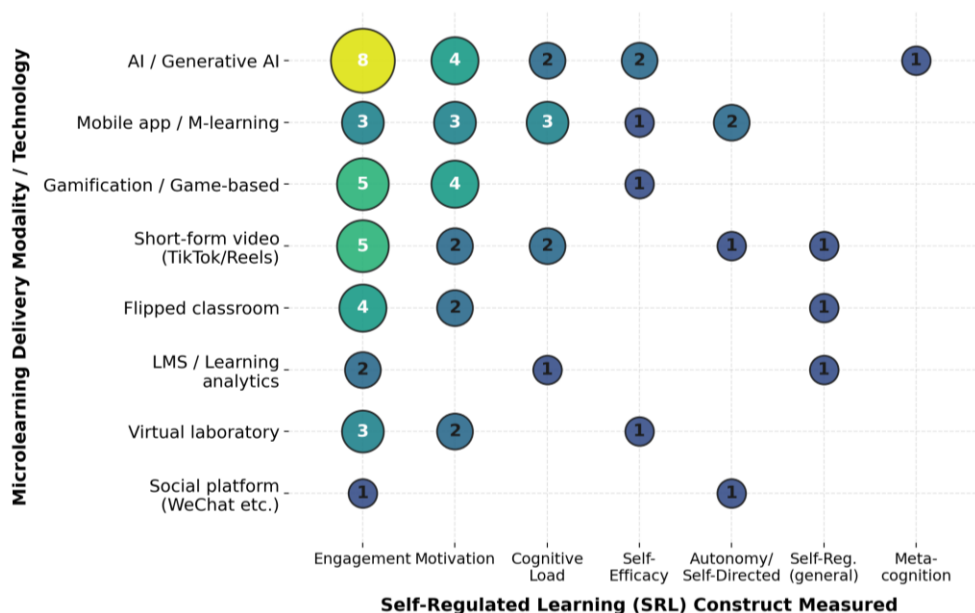


Figure 4: Research Map: Association Between Microlearning Delivery Modality and SRL Constructs

Several patterns stand out in Figure 4. First, the largest cluster forms at the intersection of AI-generative/chatbot modalities and engagement (8 studies), suggesting that AI-driven personalization and interactivity is the dominant trend in recent microlearning research. Second, gamification shows a strong link with both engagement (5 studies) and motivation (4 studies), consistent with how game-design elements are inherently built to drive active involvement. Third, metacognition and general self-regulation appear to be the constructs least explicitly mapped to any specific modality. They show up in only a handful of combinations, at a frequency of one to two studies, which points to a research gap discussed further below.

RQ1 Findings: Design Characteristics and Modalities of Microlearning

Addressing RQ1, Table 2 classifies the 49 included studies by the microlearning delivery modality/technology implemented (categories are non-exclusive, so percentages exceed 100%).

Table 2: Classification of Microlearning Delivery Modalities (Addressing RQ1)

Delivery Modality / Technology	n	%	Notable Design Characteristics
Generative AI / chatbot	10	20.4 %	Content personalization, real-time adaptive feedback, automated atomization of material into small units
Mobile app / m-learning	7	14.3 %	Just-in-time accessibility, learning-on-the-go, scheduled notifications
Gamification / game-based	7	14.3 %	Points/badges/challenges, instant feedback, progressive narrative
Short-form video (TikTok/Reels etc.)	5	10.2 %	Very short duration (< 3 minutes), visual-narrative format, distribution via social media platforms
Flipped classroom integrated with microlearning	5	10.2 %	Short content studied independently before class, class time devoted to application/discussion
LMS / learning analytics	3	6.1%	Short structured modules within a learning management system, granular activity tracking
Virtual laboratory / simulation	3	6.1%	Repeated short simulated practice, immediate performance feedback
Social/messaging platform (e.g., WeChat)	2	4.1%	Distribution through messaging apps already familiar to students
Not coded to a specific modality	17	34.7 %	Microlearning described in general terms without naming a specific technology/platform

Three design characteristics recur consistently across modalities in the corpus: (1) unit duration is consistently kept short (typically under 15 minutes, with some video formats under 3 minutes); (2) content follows a modular structure that supports repetition and non-linear access; and (3) there is a visible shift from static-media modalities (e.g., pre-produced documents or videos), dominant in earlier studies in the review period, toward adaptive and generative modalities (AI, dynamic personalization) in studies published between 2024 and 2026, mirroring a broader technological shift across higher education over that period.



RQ2 Findings: The Influence of Microlearning on Self-Regulated Learning Constructs

Addressing RQ2, Table 3 classifies the frequency and reported direction of effect for each SRL construct across the 49 included studies.

Table 3: Classification of Findings by SRL Construct (Addressing RQ2)

SRL Construct	n	%	Reported Direction of Effect
Engagement (behavioral, cognitive, emotional)	36	73.5 %	Predominantly reports improvement; a small subset reports mixed results depending on implementation design
Learning motivation (intrinsic & extrinsic)	21	42.9 %	Predominantly reports improvement, especially with gamification and AI-personalized modalities
Cognitive load (as a related mechanism)	9	18.4 %	Predominantly reports reduced extraneous cognitive load, supporting retention and comprehension
Self-efficacy	6	12.2 %	Predominantly reports improvement, particularly with flipped-classroom and simulation designs
Autonomy / self-directed learning	4	8.2%	Reported as improved, but rarely measured with a dedicated validated instrument
Self-regulation (general)	4	8.2%	Reported positively, but mostly at a conceptual/descriptive level rather than measured quantitatively
Metacognition	1	2.0%	Only one study explicitly linked chatbot-based microlearning to metacognitive processes

Engagement is the most frequently reported construct (36 of 49 studies; 73.5%), spanning behavioral (active participation), cognitive (mental effort and deep-learning strategies), and emotional (positive affect toward the learning process) dimensions. Motivation ranks second (21 studies; 42.9%), with gamification and AI-based personalization emerging as the modalities most consistently linked to motivational gains. By contrast, the constructs conceptually closest to the core of self-regulated learning (autonomy/self-directed learning, general self-regulation, and metacognition) turn out to be the least directly measured (8.2%, 8.2%, and 2.0% of included studies, respectively). This points to a real gap between how often studies frame themselves around "self-regulated

learning" and how deeply they actually measure the core constructs that term is meant to capture.

Drawing on the narrative synthesis of the full corpus, four principal mechanisms emerge to explain how the design characteristics in Table 2 translate into the SRL outcomes in Table 3: reduced cognitive load through short, focused content units; spaced repetition and retrieval practice through modular, repeatable structure; content personalization and adaptive feedback, particularly with generative-AI modalities; and greater flexibility and learner control through just-in-time accessibility. Figure 5 presents a synthesis framework that visualizes how these three layers connect.

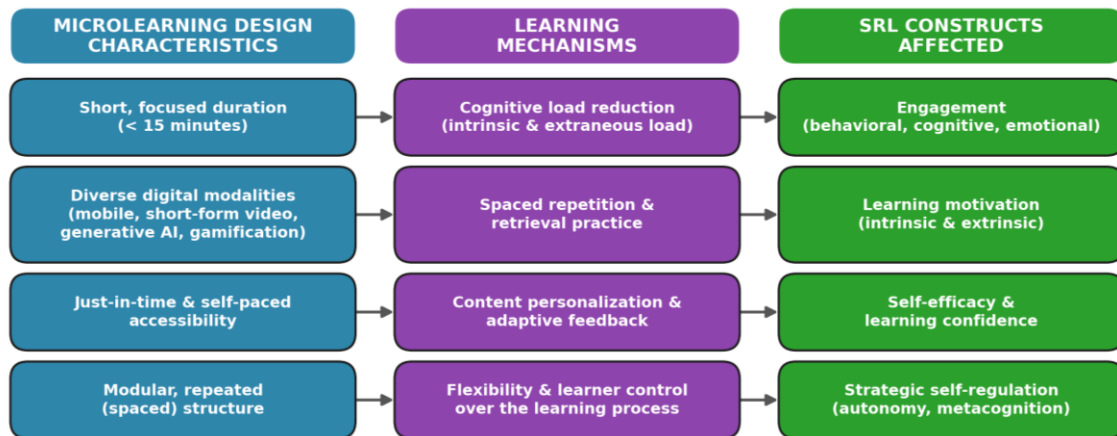


Figure 5: Synthesis Framework: From Microlearning Design Characteristics to SRL Constructs

Interpreting RQ1: Microlearning Design Characteristics in Context

The findings in Table 2 show that generative-AI/chatbot modalities are now the most-studied microlearning delivery method (20.4% of the corpus), overtaking mobile apps and gamification, which historically became established earlier. This pattern lines up with Lan and Zhou's (2025) systematic review, which documents a surge in AI research supporting self-regulated learning in higher education, and with Garzón and colleagues' (2025) meta-analysis confirming that mobile-based learning (the technological backbone of many microlearning applications) improves learning outcomes across disciplines and geographic contexts, without significant moderation by education level.

The design characteristics that hold consistent across modalities, short duration and repeated modular structure, fit with cognitive load theory's emphasis on limiting extraneous cognitive load so that working-memory capacity can be devoted to processing essential information (Hanham, 2023). Feldon and colleagues (2023) further show that cognitive load has a direct effect on learners' self-efficacy during instruction, which offers a theoretical explanation for why microlearning designs that successfully keep cognitive load in check tend to be associated with better motivational and affective outcomes, as seen in the 9 studies identified in the corpus (Table 3). At the course-design level, Javorcik and colleagues (2023) similarly show that systematically monitoring and evaluating student activity within a



microlearning course allows instructors to iteratively refine content granularity and pacing, a practice consistent with the modular, data-informed design pattern observed across the corpus.

The shift in modality from flipped classroom and conventional LMS approaches (dominant in 2021-2023 studies) toward generative AI and dynamic personalization (dominant in 2024-2026 studies) also echoes Tlili and colleagues' (2024) meta-analysis of mobile-learning pedagogical approaches, which found that adaptive and personalized approaches produced larger effect sizes than generic mobile learning that is not tailored to individual learner needs.

Interpreting RQ2: Mechanisms of Influence on Self-Regulated Learning

The dominance of engagement as the most-reported construct (73.5% of studies) is consistent with Bergdahl and colleagues' (2024) systematic review of how student engagement is measured in learning-analytics research, which similarly found that behavioral engagement (observable activity captured in log data) is far more commonly operationalized than cognitive or emotional engagement. The same pattern is visible in most studies in this corpus, which rely on participation and task-completion metrics as their primary engagement indicators.

On motivation, the finding that gamification and AI personalization are most consistently associated with motivational gains (Table 3 and Figure 4) matches Li and colleagues' (2023) meta-analysis, which confirms gamification's effectiveness in boosting motivation by satisfying basic psychological needs (competence, autonomy, relatedness), and Ratinho and Martins' (2023) systematic review, which found a similar pattern across both secondary and higher education. The personalization mechanism behind generative AI, as synthesized by Lan and Zhou (2025), works by providing adaptive feedback responsive to individual learning needs, a mechanism that conceptually maps onto the "monitoring" and "strategy adaptation" components of cyclical SRL models. This is consistent with Cardenas and colleagues' (2022) personalized learning model for academic leveling in higher education, which likewise found that adapting content difficulty and pacing to individual learner profiles improved both engagement and completion.

The most important, and most concerning, finding of this review is the gap between how studies frame themselves conceptually around "self-regulated learning" and how deeply they actually measure the core SRL constructs. Only 8.2% of studies explicitly measured autonomy/self-directed learning, and only 2.0% touched on metacognition, even though both are central to contemporary theoretical definitions of SRL (Guo, 2022; Xu et al., 2023). This gap is consistent with Xu and colleagues' (2023) and Cheng and colleagues' (2023) meta-analyses, both of which noted substantial variation in how SRL is operationalized across the studies they reviewed. Chen's (2022) meta-analytic study of SRL interventions similarly found that intervention effectiveness varied considerably depending on which SRL component, strategy use, self-efficacy, or achievement, was targeted and measured, reinforcing the need for construct-specific instrumentation. This pattern is further echoed in Panta's (2025) review of heutagogy (learner-determined learning), which stresses that

genuine learning autonomy requires measurement instruments far more specific than general proxies like "satisfaction" or "platform usage".

The modular, repeated structure that characterizes microlearning also fits the principles of spaced repetition and retrieval practice, long established as effective for long-term retention (Thompson et al., 2023). Taylor and Hung (2022), in their scoping review of microlearning's effects across education and industry sectors, likewise find that breaking content into small, repeatedly accessible units is one of the core mechanisms behind microlearning's effectiveness, a finding relevant to higher education given that eight of the nine modalities in Table 2 apply this same repeated structure.

Theoretical and Practical Implications

Theoretically, this review points to the need for a sharper conceptual distinction between "engagement" and "motivation" outcomes, which are relatively easy to capture through behavioral and attitudinal proxies, and the core SRL constructs of metacognition and strategic self-regulation, which require more sophisticated measurement (structured self-report, think-aloud protocols, or process/trace data). The synthesis framework in Figure 5 offers an initial conceptual map that future empirical work could test further, particularly to validate the mediating pathway from design characteristics through learning mechanisms to specific SRL constructs.

Practically, these findings suggest that instructional designers in higher education who want to strengthen student self-regulation, rather than surface-level engagement alone, need to deliberately build in features that prompt planning, self-monitoring, and reflection. A short, flexible format will not automatically cultivate learning independence on its own. Embedding explicit metacognitive prompts (Guo, 2022) and AI-based support specifically designed for self-regulation (Lan & Zhou, 2025) are two directions well supported by the external literature but still rarely implemented in the studies making up this corpus.

Table 4: Comparison of Corpus Findings with Supporting External Literature

Finding Theme	Pattern in the Corpus (n = 49)	Supporting External Literature (2022-2026)
Cognitive-load reduction as a core mechanism	9 studies (18.4%) link short duration to reduced extraneous cognitive load	Hanham (2023); Feldon et al. (2023)
Engagement as the dominant outcome	36 studies (73.5%) report improved engagement across behavioral, cognitive, and emotional dimensions	Bergdahl et al. (2024)
Motivation boosted by gamification & AI personalization	Gamification linked to motivation in 4-5 studies;	Li et al. (2023); Ratinho & Martins (2023); Lan & Zhou (2025)



Finding Theme	Pattern in the Corpus (n = 49)	Supporting External Literature (2022-2026)
	generative AI linked to motivation in 4 studies	
Mobile-based microlearning improves learning outcomes	7 studies (14.3%) implement mobile app/m-learning modalities	Garzón et al. (2025); Tlili et al. (2024)
Flipped classroom + microlearning strengthens self-efficacy	5 studies (10.2%) apply flipped classroom; 6 studies report self-efficacy outcomes	Sun et al. (2023)
Autonomy & self-regulation still rarely measured directly	Only 4 studies (8.2%) each for autonomy and general self-regulation constructs	Xu et al. (2023); Cheng et al. (2023); Yang et al. (2025); Panta (2025)
Modular structure fits spaced/retrieval practice	Modular, repeated design characteristic consistent across corpus modalities	Thompson et al. (2023); Taylor & Hung (2022)
Quantitative meta-analytic work for this specific HE intersection remains limited	5 studies (10.2%) are systematic reviews/conceptual frameworks; no dedicated quantitative meta-analysis of microlearning-SRL in HE yet exists	Monib et al. (2024); Cheng et al. (2023)

Limitations

This review carries several methodological limitations that should be weighed when interpreting its findings. First, the literature search used only one database (Scopus), without triangulating against others such as Web of Science or ERIC, which may have missed relevant studies indexed exclusively elsewhere. Second, screening and eligibility assessment were conducted at the abstract level by a single reviewer, without full-text access or an inter-rater reliability statistic, given the constraints of the available data. Third, heterogeneity in research design and measurement instruments across the included studies precluded a quantitative meta-analysis (pooled effect sizes); the synthesis presented here is narrative and thematic. Fourth, restricting the search to open-access documents may have introduced selection bias, since not all high-quality studies are openly accessible. Full details of these methodological limitations, including the per-study exclusion log, are provided in the accompanying PRISMA Process Report.

CONCLUSION

Main Conclusions

This systematic literature review mapped 49 included studies (drawn from 63 records returned by an open-access Scopus search) to answer two research questions about how microlearning is designed and how it relates to self-regulated learning in higher education. Addressing RQ1, generative-AI/chatbot modalities (20.4%), mobile applications (14.3%), and gamification (14.3%) emerged as the three dominant delivery modalities in the recent literature, with design characteristics that consistently emphasize short duration, repeated modular structure, and, in more recent studies, dynamic content personalization. Addressing RQ2, microlearning was most consistently associated with gains in engagement (73.5% of studies) and motivation (42.9% of studies), operating through cognitive-load reduction, spaced repetition, personalization, and greater learning flexibility; however, the core SRL constructs of autonomy, self-regulation, and metacognition remain rarely measured directly (each under 10% of studies).

Recommendations

The gap between how often studies frame themselves around "self-regulated learning" conceptually and how deeply they measure its core constructs empirically is the key takeaway researchers and instructional designers should carry forward. Future research would benefit from (1) designing microlearning interventions that explicitly target metacognitive and strategic self-regulation components rather than surface-level engagement alone; (2) using validated, construct-specific SRL instruments rather than general proxies; (3) conducting experimental studies with stronger control designs to eventually enable quantitative meta-analysis; and (4) broadening database triangulation to achieve more comprehensive literature coverage.

AUTHOR CONTRIBUTIONS

Suwarno: conceptualization, search strategy design, data curation, formal screening and coding analysis, data visualization, writing (original draft), writing (review and editing). Robinson Situmorang: supervision, methodology validation, writing (review and editing). Uwes Anis Chaeruman: supervision, validation, writing (review and editing). All authors read and approved the final manuscript.

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