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GENERATIVE ARTIFICIAL INTELLIGENCE FOR MICROLEARNING CONTENT DEVELOPMENT: OPPORTUNITIES, CHALLENGES, AND PEDAGOGICAL FRAMEWORKS

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ABSTRACT

This narrative literature review explores how Generative Artificial Intelligence (Gen AI) is used in microlearning content development, the opportunities and risks emerging from this convergence, and the pedagogical frameworks that support instructional quality and ethics. Literature was identified through structured and iterative Google Scholar searches (2018–2025) using keywords spanning Gen AI, microlearning, and content development. After two-stage screening (title–abstract and full-text), 20 core studies published in 2023–2025 were analyzed in depth, with earlier sources used only for conceptual background. The core evidence was synthesized using thematic analysis with deductive (opportunities, challenges, frameworks) and inductive coding. Findings indicate that Gen AI supports key development tasks, including learning objective formulation, outlining and storyboarding, multimodal content production, and micro-assessment generation. Opportunities include faster and more scalable production, expanded multimodal formats, and stronger support for personalization and accessibility. Key risks include inaccuracies and hallucinations, “false authority” effects in concise units, oversimplification and fragmented learning, tool/workflow fragmentation, and ethical concerns related to bias, copyright, transparency, and data privacy. The reviewed literature points to an eclectic, theory-informed approach (grounded in cognitive and multimedia learning principles, instructional design models, microlearning-specific frameworks, and inclusive design) to guide responsible Gen AI use.

KEYWORDS: Generative artificial intelligence (Gen AI); microlearning; content development; instructional design; quality assurance, thematic analysis

INTRODUCTION

The higher education landscape has undergone increasingly rapid transformation over the past decade, driven by digitalization, shifting learning patterns, and the expectations of digital-native learners. Contemporary learners, particularly Generation Z and Alpha, tend to prefer content that is concise, visual, interactive, and accessible on demand (Hug, 2022; McKee & Ntokos, 2022). These learning preferences strengthen the relevance of microlearning as an instructional approach that presents content in short, focused segments oriented toward a single, specific learning objective (Mohammed et al., 2018). In modern implementation, microlearning is often understood not merely as "breaking content into smaller pieces," but as the design of meaningful, measurable learning units that are ready to be reused across different contexts (Corbeil et al., 2021).

Various studies indicate that microlearning can support retention, just-in-time access, and a learning experience that is lighter in terms of cognitive load, especially when its design is consistent with principles of digital learning (Balasundaram et al., 2024). At the same time, the literature also suggests that microlearning has become an "increasingly strengthening trend" because it aligns with fast-paced, mobile, and needs-based ways of working and learning (Corbeil & Corbeil, 2023).

However, the primary challenge of microlearning is not merely "shortening the duration," but producing content that is well-targeted, accurate, consistent across units, and manageable. Roadmaps for microlearning implementation require design readiness (objectives, content structure, brief assessment, media, and distribution flow) and content governance so that micro-units do not become disconnected fragments (Corbeil et al., 2021). At a more technical level, the development of microlearning objects also intersects with content interoperability issues (so that micro-units can be reused across contexts, repositories, and platforms), which requires a well-organized conceptual and terminological framework (Giraldo Pérez, 2022).

Microlearning does not operate in isolation; it functions within an ecosystem involving platforms, communities, and digital learning habits. One prominent direction of development is the integration of microlearning with social media, whether as a distribution channel, a space for interaction, or a trigger for rapid learning. A recent literature review indicates a trend toward such integration, along with the need to map good practices and design risks (for example, superficial understanding if adequate scaffolding and evaluation are not provided) (Denojean-Mairet et al., 2024).

Accordingly, educators' current needs extend beyond selecting a "microlearning format." They also need to manage pedagogical quality (objectives, activities, assessment) and content quality (accuracy, consistency, language, visuals, accessibility) efficiently—while time resources and content production capabilities are often limited.

The emergence of Generative Artificial Intelligence (Gen AI), particularly Large Language Models (LLMs) and various multimodal generative tools, marks a new phase in content creation. Unlike conventional AI, which is predominantly oriented toward analysis and prediction, Gen AI can generate text, images, summaries, quizzes, activity designs, and even video scripts based on prompts (Zawacki-Richter et al., 2019; Chen et al., 2020). In education, Gen AI is viewed as having the potential to support personalization, rapid feedback, and assistance in content development (Holmes et al., 2023), while simultaneously raising issues of accuracy, bias, and shifts in educators' roles (Kasneci et al., 2023; Sullivan et al., 2023).

Several publications also emphasize that using Gen AI in educational content creation can improve efficiency and productivity, but it must be accompanied by ethical governance and quality control due to the potential for errors and bias (Faccia et al., 2023). In other words, Gen AI may act as an accelerator for content production, yet "instructional quality" is not automatically ensured simply because content can be produced quickly.

The intersection of microlearning and Gen AI is increasingly relevant because both "meet" the same needs: content that is brief, modular, quick to produce, easy to update, personal, contextual, and accessible on-demand. Some literature indicates that forms of convergence between the two are beginning to be evident in practice. A conference study on AI-assisted microlearning explains that AI is used to automate or speed up the creation of microlearning components (for example, interactive quizzes, mini lessons, short scenarios). The study also describes methods for creating microlearning elements and evaluating the accuracy of AI-generated content, while highlighting the need for human oversight to minimize errors (Saha et al., 2025). A study in Sustainability (2025) indicates that AI is part of a pedagogically informed microlearning design cycle. Within the frameworks of Cognitive Load Theory (CLT), Universal Design for Learning (UDL), and experiential learning, AI-based microlearning that combines short videos, formative quizzes, and structured discussion can improve engagement, accessibility, and performance; the authors link this to (Fadli, 2025). In research developing microlearning instructional media for Japanese grammar, Gen AI (Gemini AI, Canva Magic Media, and D-ID) was used to produce microlearning media, including storyboards, visuals, and narration. Expert validation results and student responses indicate high feasibility, yet the materials still required human revision (Noverisa et al., 2025). Several studies also show that educators have begun exploring the use of ChatGPT to create quizzes, formulate learning objectives, and develop storyboards for microlearning modules (Sullivan et al., 2023).

These early findings indicate that Gen AI functions not only as a "writing assistant," but also as a production engine for microlearning (text, visuals, assessment, video scripts) that can accelerate content development. However, precisely because production is easy and fast, the associated risks are also distinctive: shallow content, inconsistency across units, unclear learning objectives, hallucinations, bias, and issues related to academic integrity and copyright.

Although the literature on microlearning and AI in education is developing rapidly, several significant gaps remain to be addressed. First, the AI in education literature still largely emphasizes learning

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personalization and intelligent tutoring systems (Roll & Wylie, 2016; Zawacki-Richter et al., 2019), while discussions of AI's role in the instructional content development process have not been synthesized in a focused manner. Second, microlearning studies often stress effectiveness and design principles (Giurgiu, 2017; Leong et al., 2021), but they have not sufficiently examined how Gen AI can be integrated responsibly to accelerate production while maintaining the quality of micro-units. Third, the existing literature has not systematically identified patterns of Gen AI use for microlearning (the forms of application), its opportunities (efficiency and quality enhancement), its pitfalls (risks of inaccuracy, bias, over-automation, and degradation of pedagogical quality), and a pedagogical framework for quality control. Early evidence suggests that automation is promising, but it requires clear accuracy evaluation and quality control (Saha et al., 2025). Fourth, there is no strong consensus on ethical guidelines and quality assurance frameworks for Gen AI-based microlearning, particularly regarding copyright, academic integrity, bias, transparency, and the educator's role as a quality guarantor (Kasneci et al., 2023; Sullivan et al., 2023; Faccia et al., 2023).

To address these gaps, this narrative literature review aims to: (1) synthesize the literature on the use of Gen AI in microlearning content development; (2) identify the opportunities and advantages of Gen AI for accelerating and improving the quality of microlearning content development; (3) analyze the challenges, limitations, and risks of using AI-generated content for learning; and (4) develop a pedagogical framework that guides educators and instructional designers in using Gen AI effectively and responsibly.

Specifically, this review addresses the following four research questions:
RQ1: How is Gen AI currently used in microlearning content development, and which applications are used?
RQ2: What opportunities and advantages do Gen AI offer for microlearning content development?
RQ3: What challenges, limitations, and risks arise when integrating Gen AI into the microlearning content development process?
RQ4: What pedagogical frameworks and learning theories guide the development of Gen AI–assisted microlearning to ensure instructional quality and ethical standards?

Theoretically, this review enriches the body of knowledge at the intersection of instructional design, educational technology, and AI by mapping practices and early evidence of Gen AI use for microlearning, while also proposing its pedagogical framework. Practically, it helps educators and instructional designers make informed decisions about adopting Gen AI for microlearning content production, not only to be "faster," but also to be "more precise and safer." Methodologically, the narrative review approach is relevant to an interdisciplinary and rapidly evolving topic because it enables critical, conceptual synthesis across studies to generate comprehensive and actionable understanding (Greenhalgh et al., 2018).

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As demand increases for content that is instant, personalized, and mobile-friendly, educators face pressure to produce more learning materials with limited resources. In this context, the question of how to leverage Gen AI for microlearning becomes increasingly urgent. This review seeks to address that need through a comprehensive, evidence-based synthesis oriented toward quality assurance.

As the digital learning landscape evolves, microlearning that is truly “built on purpose” is increasingly needed. At the same time, Gen AI has emerged as an accelerator of content production. This situation creates an urgent need to understand how the convergence of microlearning and Gen AI is discussed in the literature, what its opportunities and risks are, and how to formulate a pedagogical framework that safeguards instructional quality and ethics. Therefore, this study employs a narrative literature review approach to synthesize findings across studies and sources, identify key themes, and formulate a framework that is both conceptual and operational (Greenhalgh et al., 2018).

METHOD

2.1 Research Method

This study employs a narrative literature review to examine how Gen AI is used in microlearning content development. This approach was chosen because the topic is rapidly evolving and interdisciplinary (instructional design, educational technology, and AI), and the available evidence spans multiple publication types. While systematic reviews benefit from established reporting guidance (e.g., PRISMA), narrative reviews do not have universally acknowledged guidelines; therefore, this review emphasizes transparency and adopts a structured approach to reduce selection bias and strengthen the credibility of the synthesis (Ferrari, 2015; Greenhalgh et al., 2018). Data were synthesized using thematic analysis to identify patterns, sub-themes, and relationships that address the research questions.

2.2 Data Sources and Literature Search Strategy

Literature searches were conducted primarily via Google Scholar, and eligible records were obtained in full-text (PDF). The search was modular and iterative across three keyword domains: (1) GenAI (e.g., “generative AI”, “ChatGPT”, “GPT”, “large language model”, “LLM”, “multimodal”), (2) microlearning (e.g., “microlearning/micro-learning”, “bite-sized learning”, “learning nuggets”, “nanolearning”), and (3) content development (e.g., “content development/creation”, “content authoring”, “instructional design”, “assessment generation”). Queries were built progressively by combining domains to broaden coverage and then increase specificity, with synonym-based iterations when results were too narrow or too broad. Consistent with narrative review recommendations, the search process was conducted in a structured and traceable manner to improve clarity and minimize selection bias (Ferrari, 2015).

2.3 Time Frame and Publication Scope

The publication time frame was set to 2018–2025 to capture foundational developments in modern microlearning and early advances in large language model–based Gen AI. However, the in-depth synthesis focused on core studies published in 2023–2025, reflecting the period after ChatGPT's public release on 30 November 2022 when Gen AI-enabled microlearning content production became more visible in the literature. Earlier publications were used selectively for definitions and conceptual framing.

2.4 Inclusion and Exclusion Criteria

Studies were included if they (a) addressed at least two of the three core components (Gen AI, microlearning, content development), (b) were credible and accessible in full text, and (c) provided substantive empirical or conceptual contributions. Eligible publication types included journal articles, conference papers, book chapters, reviews, and high-quality grey literature, limited to English-language sources. Studies were excluded if they lacked a clear connection to content development, focused only on technical machine learning without educational application, were duplicates, were methodologically unclear or non-credible, or were not accessible in full text.

2.5 Screening, Corpus Construction, and Synthesis Procedures

Screening was conducted in two stages: title–abstract screening followed by full-text screening of potentially relevant records. This transparency-oriented reporting aligns with recommendations that, although a Methods section is not mandatory in narrative reviews, documenting search and selection decisions strengthens clarity and supports rigor (Ferrari, 2015). To maintain focus, sources were prioritized based on direct relevance to the research questions, and the in-depth synthesis concentrated on 20 core documents. Key information from the core studies was systematically extracted and coded using thematic analysis (Braun & Clarke, 2006). Coding combined a deductive structure (opportunities, challenges, frameworks) with inductive coding to capture emerging patterns. Themes were iteratively refined and integrated into a pedagogical framework.

2.6 Transparency, Limitations, and Ethics

Transparency was supported through documentation of screening decisions and structured extraction in the literature matrix. Limitations include the absence of formal inter-rater reliability assessment, English-only sources, potential indexing bias from Google Scholar, and the fast-changing Gen AI literature. The study did not involve human participants and therefore did not require ethical clearance; academic integrity was maintained through accurate attribution and clear reporting of limitations.

3. FINDINGS AND DISCUSSIONS

3.1 Research Question 1

RQ1: How is Gen AI currently used in microlearning content development, and which applications are used?

From the reviewed articles, the use of Gen AI for microlearning tends to follow an end-to-end workflow: (1) planning (objectives, outline, storyboard), (2) multimodal content production (text, visuals, narration, short video), (3) micro-assessment (short quizzes/practice), and (4) feedback-based refinement. Gen AI has transformed microlearning content development by shifting processes that were previously manual and time-consuming into systems that are automated, personalized, and adaptive. Gen AI is integrated across multiple stages of instructional design to improve efficiency and pedagogical effectiveness.

3.1.1 Automating Outline Development and Text Content

The use of Gen AI in higher education has demonstrated significant potential in automating multiple aspects of learning material development. This technology is used to automate routine tasks such as generating quizzes, interactive simulations, personalized learning materials, and providing real-time feedback to students (Faccia et al., 2023). At a broader level, Gen AI can transform complex business documents such as PDFs, Word files, and Excel spreadsheets into learning modules in the form of slides and quizzes automatically, while also conducting searches for credible online sources with multilingual support (Mattei, 2025). These automation capabilities include generating multiple-choice quizzes from YouTube video transcripts (Paunovic, 2025), extracting specific video segments as answers to students' questions without manual searching (Velamakanni & Saha, 2025), and transforming long lecture recordings into interactive flashcards, mini summaries, and scenario-based exercises instantly (Saha et al., 2025).

Beyond content automation, Gen AI also plays a role in strategic planning and learning design. The technology can read teaching materials automatically, map key concepts, and generate syllabi and learning objectives aligned with educational taxonomies (Ferreira, 2025; Noverisa et al., 2025). The integration of Gen AI in the development of microlearning media for Japanese language learning, for example, has shown its effectiveness for storyboard creation, visual content generation, and narration (Noverisa et al., 2025). In addition, Gen AI functions as a performance-enabling partner that facilitates rapid course mapping, rubric design, and the automatic linking of activities across modules (Choi et al., 2024). Other capabilities include generating content outlines, drafting assessment instructions, and automatically mapping learning outcomes to external standards (Ullman et al., 2024), creating AI roleplay activities and self-correcting quizzes (Forsström & Sagersten, 2024), and providing text-to-quiz features, interactive simulations, multilingual translation of materials, and AI-based personal coaching assistants (Moore, 2025). Thus, Gen AI not only increases efficiency in developing learning materials, but also opens opportunities for deeper personalization and interactivity in the educational process.

3.1.2 Multimodal Content Production

Advances in Gen AI have enabled substantial ease in producing multimodal content for learning purposes, particularly in generating visual and audio elements without requiring advanced technical expertise. Text-to-image technology enables educators to generate relevant slide illustrations automatically, while AI Presenter tools can be used to produce natural-sounding narration for learning videos. In addition, text-to-speech (TTS) technologies have created new opportunities for producing educational podcasts that students can access easily (Noverisa et al., 2025). Integrating multiple modalities not only enriches the learning experience, but also improves accessibility for students with diverse learning preferences and styles. Furthermore, Gen AI contributes to richer learning media by automatically generating engaging graphs, tables, and visualizations, which has been shown to clarify difficult and abstract concepts effectively (Monib et al., 2024). Accordingly, Gen AI-based multimodal content production not only simplifies the development process, but also enhances pedagogical quality through more comprehensive and engaging representations of information.

3.1.3 Automated Assessment Generation

Gen AI has demonstrated high effectiveness in automating the development of learning assessments, particularly in generating evaluation instruments such as multiple-choice quizzes, digital flashcards, and scoring rubrics based on uploaded materials or video transcripts. Research findings indicate that the quality of AI-generated quizzes can be comparable to quizzes created by human instructors (Noverisa et al., 2025), suggesting the pedagogical validity of AI-based assessment instruments. The use of Gen AI for quiz generation has been widely adopted across educational contexts (Faccia et al., 2023; Mattei, 2025; Saha et al., 2025; Moore, 2025; Forsström & Sagersten, 2024), including the conversion of YouTube video transcripts into structured multiple-choice quizzes (Paunovic, 2025). This technology also facilitates the migration of traditional content into more interactive and accessible quiz formats (Reynold & Dolasinski, 2024). Beyond question generation, Gen AI can design comprehensive and standardized scoring rubrics (Choi et al., 2024), supporting consistency and objectivity in learning evaluation. Therefore, Gen AI-based automated assessment generation not only improves instructors’ efficiency in preparing evaluation instruments, but also supports quality and diversity in assessment formats that can be adapted to students’ learning needs.

3.1.4 Personalization and Adaptive Learning Pathways

The implementation of artificial intelligence in education has introduced new dimensions of learning personalization through its ability to analyze learner data and create adaptive learning pathways tailored to individual needs. AI technologies can recommend remedial materials automatically when students have not mastered specific concepts, while enabling high-performing students to skip basic material they have already mastered, thereby maximizing the efficiency of the learning process (Noverisa et al., 2025). This personalization is strengthened by AI’s ability to provide learning materials aligned with students’ individual profiles and progress, as well as real-time feedback that allows students to promptly correct errors and deepen their understanding (Faccia et al., 2023). Furthermore, AI systems can provide adaptive personal feedback that dynamically adjusts the level of complexity and the type of support based on students’ responses and development (Monib et al., 2025). Another important aspect is cognitive optimization through algorithms that manage spaced repetition schedules based on individual forgetting rates, thereby significantly improving long-term knowledge retention (Kravchenko & Cherninskyi, 2025). Thus, AI-based personalization and adaptive learning

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pathways not only accommodate differences in students' abilities and learning pace, but also optimize cognitive processes to achieve more effective and sustainable learning outcomes.

3.1.5 Extracting Complex Materials into Micro Units

One significant contribution of Gen AI in learning material development is its ability to extract and transform complex content into micro-units that are easier for students to process. AI technologies such as Whisper have been used to automatically transcribe long-duration lectures, while Natural Language Processing (NLP) algorithms enable the segmentation of these videos into short clips that are relevant to students' specific questions (Noverisa et al., 2025). This process involves not only transcription and segmentation, but also Gen AI's ability to summarize complex material into bite-sized units that support gradual comprehension (Noverisa et al., 2025). Moreover, Gen AI can convert long lecture videos into structured short video segments in reels format without losing the essence of the original content delivered by the instructor (Stavrinou et al., 2025), and automatically extract specific video segments as direct responses to students' questions without manual searching (Velamakanni & Saha, 2025). In language and literature learning contexts, the technology also supports small, focused tasks, such as analyzing a single metaphor or identifying tone in a single stanza through digital media (Ojochegbe, 2025). An important pattern identified is the use of AI to break dense materials such as case studies into concise, more accessible units that function as a bridge toward deeper discussion without replacing the need for understanding the full material (Fadli, 2025). Accordingly, AI-based extraction of complex materials into micro-units not only enhances the accessibility of learning content, but also supports the microlearning approach that has been shown to be effective in modern educational contexts.

3.1.6 Gen AI Applications and Tools in Microlearning Content Development

The AI Tool Ecosystem for Multimodal Content Production

The implementation of Gen AI in microlearning development involves a diverse and specialized tool ecosystem, with OpenAI's GPT models dominating multiple content production functions. ChatGPT (GPT-3.5, GPT-4, and GPT-4o) appears as the most frequently used tool for foundational tasks such as creating course maps, drafting text content, developing scoring rubrics, and generating interactive quizzes (Choi et al., 2024; Pal, 2025; Reynolds & Dolasinski, 2024; Ullmann et al., 2024). GPT-4 and its variants (GPT-4o, GPT-4o-mini) are used for more complex tasks such as automated video segmentation in the ReelsEd system (Stavrinou et al., 2025), generating learning modules from business documents (Mattei, 2025), and refining transcripts and producing interactive learning elements (Saha et al., 2025; Velamakanni & Saha, 2025). Other large language models such as Llama-3.3-70B-Versatile are integrated into the MentorIA adaptive learning architecture for concept mapping and automated syllabus generation (Ferreira et al., 2025), while GPT-Neo and the Transformers library from Hugging Face are used for personalized higher education applications (Faccia et al., 2023).

For visual content production, DALL-E 3 is used to create illustrative images for learning slides (Mattei, 2025), while Midjourney is selected to generate consistent illustrations in professional training contexts (Forsström & Sagersten, 2024). Canva Magic Media and Canva Magic Write appear as

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popular tools that combine text-to-image generation with visual design capabilities, used both for Japanese microlearning illustrations (Noverisa et al., 2025) and to enrich media within learning modules (Monib et al., 2024; Moore, 2025). The Canva platform is also used to design and distribute micro-content in an integrated manner (Monib et al., 2024). Specialized visualization tools such as Napkin AI are used to generate research graphics, while Gamma is applied during the needs-mining stage (Monib et al., 2025).

Learning Platforms and Specialized Tools

Dedicated microlearning platforms such as 7Taps have emerged as integrated solutions with AI-assisted features that facilitate the migration of traditional content into concise quiz and text formats (Reynolds & Dolasinski, 2024) and enable inclusive learning design through visual modification and bias elimination (Pal, 2025). Adaptive learning systems such as ReelsEd integrate GPT-4 for automated segmentation and labeling of short videos derived from long lecture recordings (Stavrinou et al., 2025), while enterprise platforms such as the one developed by Mattei (2025) use GPT-4.1 for summarizing business content, Tavily AI for searching credible research, and FastAPI for backend integration. The MentorIA architecture represents a comprehensive approach by leveraging Llama-3.3-70B-Versatile for adaptive learning that maps concepts and generates learning objectives aligned with educational taxonomies (Ferreira et al., 2025).

Other specialized tools include virtual assistants such as Cognii and MosaChat-AI for interactive tutoring (Faccia et al., 2023), Teacher Matic for automating instructional tasks (Faccia et al., 2023; Ullmann et al., 2024), and Khanmigo from Khan Academy integrated into a learning ecosystem (Ullmann et al., 2024). For preservice teachers, tool suites such as Magic School, Diffit, and Brisk Teaching are used for brainstorming, text simplification, and self-reflection (Kohnke, 2025). OpenAI Codex is applied specifically for code generation in programming education contexts (Faccia et al., 2023), while Coursera AI Coach and Moodle AI Plugins provide personalization support within existing LMS platforms (Moore, 2025).

Technical Tools for Media Processing

For audio and video processing, OpenAI's Whisper dominates as an automated transcription tool that converts long lecture recordings into structured text for further processing (Saha et al., 2025; Velamakanni & Saha, 2025). FFmpeg is used to extract and manipulate specific video segments (Velamakanni & Saha, 2025), while D-ID AI Presenter produces avatar narration for audiovisual content (Noverisa et al., 2025). Synthesia enables AI video creation without direct recording (Moore, 2025), and CapCut is used for video editing in instructional design contexts (Monib et al., 2025). The text-embedding-ada-002 model is applied for semantic matching in automated video search systems (Velamakanni & Saha, 2025).

Supporting Tools and Utilities

Several supporting tools are used to improve quality and efficiency in the development process. Grammarly and editGPT are used for language improvement and editing (Kohnke, 2025; Kravchenko & Cherninskyi, 2025), while scite_ is used to search academic literature (Kravchenko & Cherninskyi, 2025). NoteBookLM appears as a knowledge management tool in instructional design (Monib et al., 2025). LMS platforms such as Blackboard with AI Design Assistant and Moodle with DALL-E and Stable Diffusion plugins integrate AI capabilities directly into existing learning infrastructure (Moore, 2025; Ullmann et al., 2024). Vista Create and Adobe Express are used as visual production alternatives (Reynolds & Dolasinski, 2024), while Vimeo provides hosting for video and audio content (Reynolds & Dolasinski, 2024).

API Integration and Technical Frameworks

Technical implementation often involves API (Application Programming Interface) integration and programming frameworks. A Python Flask API is used to build an application interface that leverages GPT-4o-mini to generate automated quizzes from YouTube transcripts (Paunovic, 2025). FastAPI is selected as the backend framework for an enterprise platform integrating multiple AI services (Mattei, 2025). Integrated Python scripts are used to orchestrate pipelines that connect Whisper, ChatGPT, and other components within an automated content creation system (Saha et al., 2025). CustomGPT is developed for specific needs such as course selection in professional training (Forsström & Sagersten, 2024). The OpenLearning platform is used as a deployment environment for the MIND model that integrates AI into instructional design (Monib et al., 2025).

Implications of a Heterogeneous Tool Ecosystem

The diversity of tools used across studies reflects three realities of AI implementation in microlearning. First, there is no one-size-fits-all solution, each learning context requires a tailored combination of tools, such as using D-ID for avatar narration in language learning (Noverisa et al., 2025) versus ReelsEd for lecture video segmentation (Stavrinou et al., 2025). Second, the dominance of the OpenAI ecosystem (ChatGPT, GPT-4, Whisper, DALL-E) indicates a concentration of capabilities within a single provider, raising questions about technological dependence, vendor lock-in, and long-term cost implications. Third, integrating heterogeneous tools, from learning platforms (7Taps, OpenLearning) to technical tools (FFmpeg, Python APIs) and utilities (Grammarly, scite_), underscores technical complexity and the need for high multi-tool competence among content developers. The system fragmentation challenges identified in several studies (Ferreira et al., 2025; Reynolds & Dolasinski, 2024) can be understood as a direct consequence of a tool ecosystem that is not yet seamlessly integrated, requiring substantial manual orchestration to create a coherent production workflow.

3.1.7 Discussion

Findings for RQ1 indicate that the use of Gen AI in microlearning content development has shifted from simple *tool-based assistance* (e.g., writing support) to more systematic integration across an end-to-end workflow. Across the reviewed studies, Gen AI is used from planning (course maps, outlines,

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storyboards, learning objectives), to content production (text, summaries, visuals, narration, short video scripts), to micro-assessment (quizzes, flashcards, rubrics) and feedback-based refinement. This pattern suggests that Gen AI increasingly functions as an "authoring engine" that accelerates micro-unit production while enabling greater personalization and adaptivity, for example through remedial recommendations, real-time feedback, and *spaced repetition* scheduling (Faccia et al., 2023; Choi et al., 2024; Noverisa et al., 2025; Kravchenko & Cherninskyi, 2025). However, several studies also emphasize that such automation still requires *human-in-the-loop* oversight to ensure alignment with learning objectives, cross-unit consistency, and pedagogical quality control.

In terms of applications, the ecosystem appears heterogeneous yet concentrated around a few core stacks. GPT/ChatGPT models (GPT-3.5/4/4o and variants) are the most dominant for drafting, assessment design, and cross-format content orchestration, while specialized media tools support multimodal production, such as DALL-E/Midjourney/Canva for visuals, Whisper for transcription, and FFmpeg and embedding-based systems for video segmentation and retrieval (Reynolds & Dolasinski, 2024; Ullmann et al., 2024; Saha et al., 2025; Velamakanni & Saha, 2025; Mattei, 2025; Stavrinou et al., 2025). In addition, several microlearning platforms and LMS environments are beginning to embed AI features to migrate traditional content into micro-content, while technical integration is often implemented via APIs and frameworks such as Flask or FastAPI to unify multiple AI services into a single production pipeline (Reynolds & Dolasinski, 2024; Paunovic, 2025; Mattei, 2025). Overall, this evidence suggests that current Gen AI use in microlearning is not merely a matter of selecting a single application, but of assembling a tool ecosystem that supports rapid production alongside quality assurance and content governance needs.

3.2 Research Question 2

RQ2: What opportunities and advantages do Gen AI offer for microlearning content development?

Using Gen AI in microlearning development offers a range of opportunities for educators and instructional designers, especially in meeting the need for content that can be updated quickly, stays accurate, and fits clear learning goals. With limited time and the need for varied formats (text, visuals, activities, short checks), Gen AI can speed up production while also improving quality by supporting idea generation, helping organize structure, and polishing language and media.

3.2.1 Automation and Faster Production of Microlearning Content

Gen AI provides strong opportunities to automate and speed up microlearning content development, which has traditionally required substantial time and resources. It can accelerate the creation of learning media by automatically generating storyboards, visual elements, and audio narration (Noverisa et al., 2025). AI's ability to turn hundreds of minutes of lecture recordings into structured microlearning materials in only 45 minutes shows a dramatic improvement in time efficiency for educational institutions (Saha et al., 2025). AI can also extract specific video segments automatically as direct answers to students' questions, without manual searching, enabling efficient non-linear access

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(Velamakanni & Saha, 2025). In corporate training, AI has been shown to reduce manual workload in content preparation and to support instant multilingual translation of training materials (Mattei, 2025).

Work efficiency is the most consistent opportunity highlighted in studies on Gen AI for microlearning. Integrating Gen AI can significantly boost productivity by automating routine tasks such as creating quizzes, assignments, and simulations, allowing instructors to focus more on higher-level pedagogical decisions (Faccia et al., 2023). Self-correcting quizzes help save instructor time while ensuring learners truly absorb the material (Forsström & Sagersten, 2024). Gen AI is also used to speed up other repetitive tasks, such as drafting short explanations, generating examples, and preparing content variations for short learning units. In higher education, this acceleration matters because microlearning often requires producing many small units, each with clear objectives and a check for understanding (Faccia et al., 2023; Choi et al., 2024). Conceptually, some studies frame Gen AI not only as a "fast writing" tool, but as part of a course production system that supports drafting while reducing time-to-content (Ullmann et al., 2024). Platforms such as 7Taps, which include AI support, help educators move from traditional approaches to microlearning more easily through strong design assistance features (Reynolds & Dolasinski, 2024). In professional training, microlearning supported by Gen AI also appears as a practical strategy for making skills training more affordable and scalable (Forsström & Sagersten, 2024).

Beyond faster production, AI can quickly generate a reasonable content skeleton and act as a thinking partner that helps educators expand and refine their ideas (Ullmann et al., 2024). ChatGPT has been shown to be effective for rapidly producing course maps that align learning objectives, activities, and assessment in a systematic way (Choi et al., 2024). AI can map key concepts from teaching materials to generate syllabus drafts and learning objectives automatically, and it can also create adaptive content blocks in real time based on learners' cognitive profiles (Ferreira et al., 2025). The use of prompting frameworks can support more inclusive, fair, and less biased content through iterative design processes (Pal, 2025). As production becomes faster, attention shifts from "how quickly content can be created" to "which formats can be produced consistently and at scale." Gen AI makes it easier to expand microlearning artifacts into multimodal packages that include short text, narration, simple visuals, and short videos. Studies on short-form educational videos show that Gen AI can support both design and production, for example by helping with scripts, video structure, and visual ideas, making microlearning videos easier to produce at larger scale (Velamakanni & Saha, 2025; Stavrinou et al., 2025). Combining multiple AI tools is also used to build concise but structured microlearning media through storyboards, visuals, and narration (Noverisa et al., 2025). This supports the view that microlearning is not simply "short content," but a designed micro-experience that can take many forms, and Gen AI expands the capacity to produce those formats (Reynolds & Dolasinski, 2024; Moore, 2025).

3.2.2 AI-Based Personalization, Adaptation, and Accessibility

One major advantage of Gen AI is its ability to create adaptive learning pathways in real time. Content can be adjusted dynamically based on students' cognitive profiles and learning progress (Ferreira et al., 2025). AI-based learning architectures allow high-performing students to skip basic materials, while students who struggle receive automatically reconfigured remedial content (Ferreira et al., 2025). AI can act as an orchestrator that delivers microlearning assets predictively to close knowledge gaps quickly (Zulfa et al., 2024). Research also suggests that AI tutors can help students learn twice as much in a shorter time compared with traditional classroom methods (Moore, 2025).

In teacher professional development, AI functions as a creative assistant for brainstorming lesson ideas and as a "co-regulator" that provides instant feedback to support self-directed learning (Kohnke, 2025). For preservice teachers, Gen AI-supported microlearning pathways are seen as a more independent and adaptive form of professional development support (Kohnke, 2025). This shows that personalization is relevant not only for students, but also for strengthening educators' competencies.

Gen AI-assisted microlearning can also improve accessibility and support learners with diverse needs. In inclusive design contexts, systems thinking and attention to equity encourage the use of Gen AI to broaden representation, reduce language barriers, and design fairer learning experiences (Pal, 2025). Simpler language and more modular learning units can make materials easier to access for different learner groups. Even so, design models that integrate AI and microlearning still need to maintain coherence and a complete learning experience so that learning outcomes can improve effectively (Monib et al., 2025).

3.2.3 Cognitive Optimization and Increased Engagement

Gen AI supports cognitive optimization through algorithms that adjust spaced repetition intervals and content difficulty based on individual performance analytics (Kravchenko & Cherninskyi, 2025). AI systems such as ReelsEd, which uses GPT-4, have been shown to outperform traditional long-form videos in learner engagement, quiz performance, and task efficiency without increasing cognitive load (Stavrinou et al., 2025). A six-week microlearning implementation showed an increase in learner engagement from 60% to 95%, with students reporting greater confidence in experimenting with sentence structures because tasks were small and focused (Ojochegbe, 2025). AI also helps increase media richness, which can clarify complex concepts and improve learner satisfaction and understanding (Monib et al., 2024).

3.2.4 Discussion

Findings across studies suggest that integrating Gen AI into microlearning content development brings three main, mutually reinforcing opportunities: production efficiency, learning personalization, and cognitive optimization. The first dimension, automating production, supports the view that Gen AI is not simply a tool for faster writing, but a transformative part of the production system. It can turn hundreds of minutes of lecture recordings into structured microlearning units in 45 minutes (Saha et

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al., 2025) and automate self-correcting quizzes that save instructors' time (Forsström & Sagersten, 2024). This efficiency allows educators to shift attention from repetitive technical tasks to higher-level pedagogical decisions (Faccia et al., 2023; Ullmann et al., 2024), while also expanding capacity to produce scalable multimodal packages—from text to short videos (Noverisa et al., 2025; Stavrinou et al., 2025).

The second dimension, personalization and accessibility, highlights the potential to democratize learning through adaptive pathways that adjust content in real time based on students' cognitive profiles (Ferreira et al., 2025) and reduce language barriers for diverse learners (Pal, 2025). Evidence that AI tutors can help students learn twice as fast as traditional methods (Moore, 2025) suggests that personalization is not only about convenience, but also about measurable pedagogical effectiveness. The third dimension, cognitive optimization, shows that AI can apply neuroscience-informed principles such as spaced repetition and adaptive difficulty in a systematic way (Kravchenko & Cherninskyi, 2025). This has been linked to increased learner engagement from 60% to 95% in a six-week implementation (Ojochegbe, 2025) and to better quiz performance than traditional long-form videos without adding cognitive load (Stavrinou et al., 2025).

However, these three opportunity dimensions do not stand alone. High production efficiency matters only when paired with strict quality control, strong personalization requires design that maintains learning coherence (Monib et al., 2025), and cognitive optimization depends on educators' ability to curate and verify AI outputs (Choi et al., 2024). In this sense, Gen AI's opportunities in microlearning are conditional. They are realized most fully only when supported by instructional design literacy, adequate technical infrastructure, and clear institutional policies for content verification and AI governance.

3.3 Research Question 3

RQ3: What challenges, limitations, and risks arise when integrating Gen AI into the microlearning content development process?

Behind the opportunities it offers, integrating Gen AI into microlearning content development also brings challenges and risks that need to be examined critically. Faster and easier production can create problems with accuracy, consistency across units, and clear learning goals, especially when verification and quality control are not well designed. For that reason, this section discusses the key challenges, limitations, and risks that need to be anticipated at the content, pedagogy, and governance levels of Gen AI use.

3.3.1 Content Quality and Accuracy Risks

A central challenge in using Gen AI is the risk of producing content that looks credible but contains false information or hallucinations (Ullmann et al., 2024; Paunovic, 2025). Short microlearning units can feel persuasive, so when AI makes mistakes, the risk of "false authority" increases, learners may accept the output as correct because it is presented neatly and concisely (Choi et al., 2024; Ullmann et al., 2024). ChatGPT is also often weak in understanding context, such as suggesting physical activities for an online class, and it sometimes fabricates literature references that do not exist (Choi et al., 2024). Even when overall accuracy seems acceptable, students still report finding incorrect information in AI-generated content on multiple occasions. In microlearning video, the risk becomes stronger because the shorter the content, the higher the demand for precision (Saha et al., 2025). Therefore, several studies stress the need for strict verification mechanisms and quality control, rather than relying only on production efficiency (Choi et al., 2024; Ullmann et al., 2024).

3.3.2 Pedagogical Risks: Oversimplification and Learning Fragmentation

The most common pedagogical concern is oversimplification, where quickly produced microlearning becomes too shallow or too fragmented to build integrated understanding. This concern is especially strong in short-video production, "concise" can turn into "reductive" if the design does not lock in one meaningful objective and does not provide the right short practice activities (Saha et al., 2025; Stavrinou et al., 2025). Knowledge fragmentation can occur when learners struggle to connect small tasks to the bigger picture or to the main learning goals (Ojochegbe, 2025; Monib et al., 2024). There is also a risk of excessive simplification or factual distortion in highly compressed video formats, along with the loss of nuance in the material (Stavrinou et al., 2025). In adaptive microlearning architectures, studies also warn about fragmented learning experiences when too many tools or components are used without clear design orchestration, which can blur both the educator's role and the learning objectives (Ferreira et al., 2025).

3.3.3 Learners' Cognitive and Affective Risks

Using AI without critical literacy can lead to shallow understanding of the material (Kohnke, 2025). "Information anxiety" may arise when content is segmented too extremely, as well as a "personalization trap," where too much tailoring can limit learners' cognitive flexibility to adapt to unfamiliar formats (Kravchenko & Cherninskyi, 2025). Microlearning designs, especially those heavily based on short quizzes, can also trigger pressure or anxiety for some learners, so care is needed in how micro-assessments are placed (Kravchenko & Cherninskyi, 2025). A pace that is too fast in small units can make it harder to grasp very complex concepts (Monib et al., 2024). There are also concerns about reduced learner agency if learning pathways are fully driven by algorithms without transparency (Zulfa et al., 2024). Over-reliance on automation can reduce human interaction and the depth of critical analysis, which may result in surface-level understanding (Saha et al., 2025).

3.3.4 System Fragmentation and Integration Challenges

Tool fragmentation is a practical barrier, as planning, personalization, and evaluation systems are often disconnected from one another (Ferreira et al., 2025). A scattered tool ecosystem makes it difficult to standardize workflows and increases coordination workload (Ferreira et al., 2025; Reynolds et al., 2024). Early trials also report issues such as inadequate text blocks and quiz difficulty levels that do not fit well (Ferreira et al., 2025). Balancing flexibility with pedagogical quality when working with large numbers of participants is another challenge (Forsström & Sagersten, 2024). Rapid technological change can also make learning materials become outdated quickly (Forsström & Sagersten, 2024).

3.3.5 Ethical Risks: Bias, Fairness, and Copyright

Bias and fairness appear as major concerns, especially in examples, framing, or language that may exclude certain groups. AI often generates content with limited cultural sensitivity and weak visual diversity if prompts are not designed very specifically (Pal, 2025). Studies on inclusive learning design treat bias as a design issue that should be addressed from the start, not fixed later (Pal, 2025). Algorithmic bias can also reinforce educational inequality (Moore, 2025; Paunovic, 2025). Beyond bias, content ownership and copyright issues stand out. Gen AI may produce material that "looks original," but licensing status, source references, and attribution are often unclear (Ullmann et al., 2024; Faccia et al., 2023). Other ethical concerns include a lack of content accountability, threats to student data privacy, and potential violations of privacy rules such as FERPA/GDPR (Faccia et al., 2023; Moore, 2025). This means faster production must be matched with clear attribution governance and citation practices.

3.3.6 Data Privacy and Security Risks

When microlearning is developed from internal materials, the risk of data leakage or misuse increases, especially in enterprise knowledge transfer contexts (Mattei, 2025; Faccia et al., 2023). Reliance on third-party APIs raises privacy and operational cost risks, as well as the possibility that confidential company or institutional data could be exposed to external servers (Mattei, 2025). These privacy and security issues become more complex when Gen AI is used with internal sources (institutional or corporate materials), because they involve sensitive data that require strong protection under relevant regulations.

3.3.7 Technical and Operational Limitations

Key technical limitations include limited input modalities (currently text-only), inefficiencies when images must be generated sequentially (causing delays), and a maximum file upload size of 420 KB (Mattei, 2025). Tool-specific constraints, such as character limits (for example, a 50-character limit in 7Taps), can restrict design complexity (Pal, 2025). AI-generated presentation styles may feel rigid and template-like, and Indonesian narration can sound unnatural when produced through text-to-speech (TTS) (Noverisa et al., 2025). Another major barrier is the time-consuming effort required to migrate or redesign content from traditional formats into microlearning modules, as well as technical difficulties in learning new tools (Reynolds & Dolasinski, 2024). Limited transparency around how AI generates content is also a challenge for understanding the production process and outcomes (Stavrinou et al., 2025).

3.3.8 Educator Readiness and Competence

Many studies emphasize that the ability to "design–curate–verify" is critical for successful Gen AI implementation. Without design literacy and clear institutional policies, Gen AI can increase

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educators' workload and confusion (Choi et al., 2024; Moore et al., 2025). The emotional and cognitive burden on instructors in managing complex self-directed learning pathways is another challenge (Kohnke, 2025). Limited institutional support and systematic pedagogical training for teachers in AI use, along with uncertainty about the legitimacy of AI resources, add further complexity (Kohnke, 2025). Educators need adequate training not only in the technical use of tools, but also in critical literacy to evaluate and curate AI-generated content.

3.3.9 Digital Divide and Accessibility

The digital divide remains a serious challenge, as low-resource institutions may struggle to implement AI technologies due to infrastructure limits such as unreliable electricity and insufficient internet access (Moore, 2025). This inequality could widen the educational gap between institutions with advanced technology access and those without. Limited peer interaction in online learning modes, as well as technical issues such as unstable internet connections, can also reduce the effectiveness of AI-based microlearning implementation (Monib et al., 2024). These accessibility challenges require careful attention so that AI technologies do not create new forms of inequality in access to quality education.

3.3.10 Discussion

Findings across studies show that the challenges of integrating Gen AI into microlearning content development are multidimensional and interconnected, forming a complex risk ecosystem that spans technical to epistemic levels. At the content quality level, the "false authority" effect, where AI-generated content appears credible but contains hallucinations or fabricated references, poses a serious threat because the concise microlearning format tends to increase learners' trust in information that is presented neatly (Choi et al., 2024; Ullmann et al., 2024; Paunovic, 2025). This risk is compounded by pedagogical challenges of oversimplification and fragmentation, where rapid production can result in content that is "reductive" rather than simply "concise," making it difficult for learners to connect small units into an integrated understanding (Velamakanni & Saha, 2025; Ojochegbe, 2025; Stavrinou et al., 2025).

Cognitive and affective factors add further complexity. Extreme content segmentation can trigger "information anxiety" and a "personalization trap" that limits cognitive flexibility, while excessive automation may reduce the depth of critical analysis and diminish learner agency (Kravchenko & Cherninskyi, 2025; Zulfa et al., 2024; Saha et al., 2025). Ethical challenges, including algorithmic bias that can reinforce inequality, limited cultural sensitivity, and ambiguous copyright status, suggest that faster production without clear governance can produce content that is structurally biased and legally problematic (Pal, 2025; Moore, 2025; Faccia et al., 2023). Privacy and data security risks, especially the leakage of sensitive information to third-party application programming interfaces (APIs) and violations of regulations such as the Family Educational Rights and Privacy Act (FERPA) and the General Data Protection Regulation (GDPR), increase the urgency of strict security protocols in enterprise learning contexts (Mattei, 2025; Faccia et al., 2023).

Technical limitations, such as restricted input modalities, template-like outputs, and unnatural narration produced through text-to-speech (TTS), indicate that current Gen AI technology is not yet fully mature for producing high-quality content without human curation (Mattei, 2025; Noverisa et al., 2025; Pal, 2025). System fragmentation and rapid technological change create operational challenges, including disconnected workflows and the risk that content becomes outdated quickly (Ferreira et al., 2025; Forsström & Sagersten, 2024). Most importantly, educator readiness is a determining factor: without the competence to "design–curate–verify" and systematic institutional support, Gen AI can increase instructors' cognitive and emotional burden rather than reduce it (Choi et al., 2024; Kohnke, 2025; Moore, 2025). Finally, the digital divide raises a fundamental equity dilemma. Institutions with limited resources not only lose access to the efficiency gains offered by AI, but also risk falling behind competitively, potentially widening gaps in educational quality (Moore, 2025; Monib et al., 2024).

Overall, these findings underline that optimism about Gen AI's potential must be balanced with critical caution. This technology is not a plug-and-play solution. It is a tool that requires robust infrastructure (technical, pedagogical, ethical, and legal), high-level design literacy, and layered quality assurance mechanisms to ensure that production efficiency does not come at the expense of pedagogical integrity and epistemic justice.

3.4 Research Question 4

RQ4: What pedagogical frameworks and learning theories guide the development of Gen AI–assisted microlearning to ensure instructional quality and ethical standards?

Studies suggest that Gen AI–assisted microlearning is not developed in an ad hoc way, but is designed with reference to specific learning theories and pedagogical frameworks. These references serve as practical guides for how to segment content, choose activity and assessment formats, keep cognitive load at an appropriate level, and ensure the learning experience remains coherent and inclusive. The following section summarizes the most frequently used theories and frameworks, and highlights how they help safeguard instructional quality and ethical use of Gen AI.

3.4.1 Cognitive Theories as the Main Foundation

Cognitive Load Theory (CLT) is the most dominant pedagogical foundation in AI-based microlearning development. It is used to justify segmenting learning materials into small units that can reduce cognitive load and improve learning efficiency (Kravchenko & Cherninskyi, 2025; Ojochegbe, 2025; Saha et al., 2025; Stavrinou et al., 2025). Mayer's Cognitive Theory of Multimedia Learning is also widely applied, especially to support dual-channel processing of visual and auditory information to optimize memory retention (Monib et al., 2024; Noverisa et al., 2025; Velamakanni & Saha, 2025). Neurocognitive mechanisms such as spaced repetition and Dual Coding Theory are also integrated to strengthen learning processes through mobile applications (Kravchenko & Cherninskyi, 2025).

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3.4.2 Constructivist Approaches and Self-Directed Learning

Constructivist principles are applied through active learner participation in building knowledge via focused tasks and social interaction (Noverisa et al., 2025; Ojochegbe, 2025). Vygotsky's constructivist learning perspective emphasizes that learners actively develop understanding through direct experience (Ojochegbe, 2025). Self-Regulated Learning (SRL) and Self-Directed Professional Development (SDPD) are used to support independent learning, especially in teacher professional development (Kohnke, 2025). Self-Determination Theory (SDT) is also applied to understand learners' intrinsic motivation in microlearning contexts (Monib et al., 2024).

3.4.3 Instructional Design Frameworks

Several traditional instructional design frameworks are adapted to integrate AI into microlearning. The ADDIE model (Analysis, Design, Development, Implementation, Evaluation) and the Successive Approximation Model (SAM) are compared with AI-enriched approaches to create more responsive designs (Moore, 2025). Wiggins and McTighe's Backward Design approach is applied by starting from the intended learning outcomes before designing activities and assessment (Choi et al., 2024). The PPE model (Planning, Production, Evaluation) from Richey and Klein is used as a systematic framework for developing microlearning media (Noverisa et al., 2025). Bloom's Taxonomy is a common reference to ensure cognitive depth in interactive quizzes and to design structured learning objectives (Forsström & Sagersten, 2024; Mattei, 2025; Moore, 2025; Ullmann et al., 2024).

3.4.4 Microlearning-Specific Frameworks

The Dolasinski and Reynolds microlearning model includes goal setting, identifying learning styles, and assessment as systematic stages of implementation (Reynolds & Dolasinski, 2024). The Elias framework is used to assess the effectiveness of microlearning units across five dimensions: learning-driven, granularity, engagement, interactivity, and personalization (Reynolds & Dolasinski, 2024). Hug's seven-dimension microlearning framework (covering learning time, content, curriculum, form, process, medium, and type) is used to design content segmentation in a comprehensive way (Saha et al., 2025). The MIND model (Microlearning Artificial Intelligence–Integrated Instructional Design) extends the TPACK framework (Technological Pedagogical Content Knowledge) into SATPACK (Situational Awareness Technological Pedagogical Content Knowledge) by adding Situational Awareness to strengthen educators' contextual awareness (Monib et al., 2025).

3.4.5 Inclusive and Adaptive Learning Approaches

Universal Design for Learning (UDL) is applied to create inclusive content that can be accessed by learners with diverse needs (Moore, 2025; Pal, 2025). Systems Thinking and Action Research methodologies are integrated to design fair learning experiences and reduce bias (Pal, 2025). The Education 5.0 concept, which is human-centered, and Augmented Intelligence (AuI) serve as foundations for developing adaptive microlearning architectures (Ferreira et al., 2025). Carvalho's Pedagogical Architecture framework integrates pedagogical approaches with software and AI to create cohesive learning systems (Ferreira et al., 2025). Adaptive learning and content personalization are emphasized to meet specific needs of higher education students (Faccia et al., 2023).

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3.4.6 Contemporary Learning Theories

George Siemens' Connectivism is used to understand learning as a process of navigating and growing networks of connections in the digital era (Zulfa et al., 2024). Expectancy-Disconfirmation Theory (EDT) is applied to measure learners' perceptions and satisfaction with the microlearning experience (Monib et al., 2024). Situational Awareness Theory (SAT) is used to examine how learners process information in dynamic learning contexts (Monib et al., 2024). The ACT-R framework (Adaptive Control of Thought—Rational) from cognitive science is applied to model human thinking processes in AI-supported automated systems (Choi et al., 2024). Andragogy theory is also referenced to understand the distinctive characteristics of adult learning in microlearning contexts (Monib et al., 2024).

3.4.7 Hybrid and Innovative Learning Models

The Just-In-Time (JIT) Knowledge concept is applied to provide timely information based on learners' needs (Mattei, 2025). Flipped Classroom, Project-Based Learning, and Networked Learning approaches are combined with microlearning to create richer learning experiences (Forsström & Sagersten, 2024). A SOLO-based syllabus design (Structure of Observed Learning Outcomes) is used to assess levels of learner understanding in a progressive way (Forsström & Sagersten, 2024). Technology Acceptance Theory is referenced in the context of using social media and technology for learning (Velamakanni & Saha, 2025).

3.4.8 Quality Evaluation Frameworks

Outcome quality dimensions—Resemblance (similarity to standards), Clarity (content clarity), and Perceived Reliability (perceived trustworthiness)—are used to evaluate AI-generated content outputs (Paunovic, 2025). The Factors Influencing Learning Outcomes (FIL) framework is applied to identify variables that affect learning effectiveness (Monib et al., 2025). The dopaminergic motivation system is also discussed to understand neurobiological mechanisms that drive engagement in microlearning (Kravchenko & Cherninskyi, 2025).

3.4.9 Discussion

Findings across studies suggest that high-quality and ethical Gen AI–assisted microlearning requires theoretical eclecticism, strategic integration of classic and contemporary pedagogical frameworks that complement one another. The dominance of Cognitive Load Theory (CLT) as a primary foundation (Kravchenko & Cherninskyi, 2025; Ojochegbe, 2025; Saha et al., 2025; Stavrinou et al., 2025) points to a strong consensus that microlearning content segmentation should be grounded in neuroscience-informed principles about human information-processing capacity, rather than driven only by technical considerations or production efficiency. The integration of Mayer's Cognitive Theory of Multimedia Learning to optimize dual visual–auditory channels (Monib et al., 2024; Noverisa et al., 2025; Velamakanni & Saha, 2025), along with mechanisms such as spaced repetition and Dual Coding Theory (Kravchenko & Cherninskyi, 2025), strengthens the argument that effective microlearning design should be evidence-based rather than intuition-driven.

At the same time, the use of Vygotskian constructivism and Self-Regulated Learning (SRL) theory (Self-Regulated Learning) (Kohnke, 2025; Noverisa et al., 2025; Ojochegbe, 2025) reflects an awareness that while AI can automate production and support personalization, learner agency and active participation remain crucial elements that should not be reduced. The adaptation of traditional instructional design frameworks such as ADDIE (Analysis, Design, Development, Implementation, Evaluation), SAM (Successive Approximation Model), and Backward Design (Choi et al., 2024; Moore, 2025; Noverisa et al., 2025) with AI integration shows efforts to bridge proven systematic approaches with new technological capabilities. Meanwhile, the frequent use of Bloom's Taxonomy as a general reference (Forsström & Sagersten, 2024; Mattei, 2025; Ullmann et al., 2024) underscores a commitment to maintaining cognitive rigor in rapidly produced content.

Microlearning-specific frameworks, such as the Dolasinski–Reynolds model, the Elias framework, Hug's seven dimensions, and the MIND model (Microlearning Artificial Intelligence–Integrated Instructional Design) that extends TPACK (Technological Pedagogical Content Knowledge) into SATPACK (Monib et al., 2025; Reynolds & Dolasinski, 2024; Saha et al., 2025), signal a shift from generic models toward frameworks tailored to the complexities of AI-assisted microlearning, with stronger emphasis on situational awareness and multidimensional evaluation. The application of Universal Design for Learning (UDL) and Systems Thinking (Moore, 2025; Pal, 2025) reflects a move away from technology-centered approaches toward human-centered design that prioritizes inclusion and equity, aligned with Education 5.0 and Augmented Intelligence (AuI) (Ferreira et al., 2025), which position AI as an augmentation rather than a replacement of human capability.

The integration of contemporary learning theories such as Siemens' Connectivism (Zulfa et al., 2024), Expectancy-Disconfirmation Theory (EDT) (Monib et al., 2024), and ACT-R (Adaptive Control of Thought—Rational) (Choi et al., 2024) indicates an effort to capture learning dynamics in a digitally networked and algorithm-mediated era, while references to Andragogy highlight the need to differentiate approaches based on adult learner characteristics (Monib et al., 2024). Hybrid approaches that combine Just-In-Time (JIT) Knowledge, Flipped Classroom, and Project-Based Learning (Forsström & Sagersten, 2024; Mattei, 2025) suggest that microlearning is not treated as a stand-alone modality, but as a component within a broader learning ecosystem. Finally, the use of quality evaluation frameworks such as the Resemblance–Clarity–Reliability dimensions (Paunovic, 2025) and the FIL framework (Factors Influencing Learning Outcomes) (Monib et al., 2025) shows recognition that without systematic quality assurance, even the most sophisticated pedagogical frameworks will not guarantee the quality of AI outputs.

Overall, these findings indicate that instructional and ethical quality in Gen AI-assisted microlearning cannot be ensured by a single theory or by advanced technology alone. Instead, it requires a thoughtful orchestration framework in which each theory or model is selected deliberately to address specific dimensions of design, production, and implementation complexity, with AI serving as an enabler guided by robust pedagogical principles and explicit ethical values.

4. CONCLUSIONS

This narrative literature review reveals that Gen AI is affecting the process of developing microlearning content, by allowing for an increase in production speed, richer multimodal formats and new opportunities for personalization and adaptive support. In the papers considered, Gen AI is not only a tool for writing text but also used to help with storyboarding, visual and audio generation, scripting of short form video and automatic micro-assessment which can save on development time and expand scalable content creation. Yet, the evidence also makes clear that speed and automation cannot ensure instructional quality. content inaccuracies and hallucinations, "false authority" effects in bite-sized chunks, oversimplification and fragmentation of learning, cognitive and affective risks for learners, system fragmentation across tools, and ethical concerns related to bias, copyright, transparency, and data privacy. These risks become more consequential in microlearning contexts because short formats demand high precision, clear objectives, and tight alignment across units.

The review highlights an important finding: high-quality, ethical use of Gen AI in microlearning depends on deliberate pedagogical planning, not simply ad hoc tool adoption. The studies examined consistently reference established educational frameworks. These include Cognitive Load Theory, multimedia learning principles, and spaced repetition, as well as constructivist and self-regulated learning approaches. Many also draw on instructional design models like ADDIE and Backward Design. Microlearning-specific frameworks and inclusive design principles such as Universal Design for Learning further complement these foundations.

Across the literature, a clear pattern emerges: Gen AI functions best as an enabling tool within a structured design and quality assurance process. This means integrating human oversight, establishing clear evaluation criteria, and implementing institutional policies that address verification, attribution, and responsible use.

Several priorities for future work become apparent from this review. First, we need stronger empirical evidence, particularly regarding learning outcomes and learner experience in real-world contexts. Second, quality assurance and ethical guidelines tailored specifically to Gen AI-assisted microlearning require further development. Finally, the field needs practical design patterns that can help educators balance the efficiency of automation with the need for pedagogical coherence and accountability.

REFERENCES

Balasundaram, S., Mathew, J., & Nair, S. (2024). Microlearning and learning performance in higher education: A post-test control group study. *Journal of Learning for Development, 11*(1), 1-14. https://files.eric.ed.gov/fulltext/EJ1423546.pdf

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77-101. https://doi.org/10.1191/1478088706qp063oa

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264-75278. https://doi.org/10.1109/ACCESS.2020.2988510

Choi, G. W., Kim, S. H., Lee, D., & Moon, J. (2024). Utilizing Generative AI for instructional design: Exploring strengths, weaknesses, opportunities, and threats. *TechTrends, 68*(4), 832–844. https://doi.org/10.1007/s11528-024-00967-w Springer Link

Corbeil, J. R., & Corbeil, M. E. (2023). *Microlearning: The "OG" or hot new trend?* EDUCAUSE Review. https://er.educause.edu/articles/2023/8/microlearning-the-og-or-hot-new-trend

Corbeil, M. E., Corbeil, J. R., & Khan, B. H. (2021). A multidimensional roadmap for implementing effective microlearning solutions. In J. R. Corbeil, B. H. Khan, & M. E. Corbeil (Eds.), *Microlearning in the digital age: The design and delivery of learning in snippets* (pp. 3–13). Routledge. https://www.taylorfrancis.com/chapters/edit/10.4324/9780367821623-2/multidimensional-roadmap-implementing-effective-microlearning-solutions-maria-elena-corbeil-joseph-rene-corbeil-badrul-khan?context=ubx&refId=08dc689d-1659-43cf-ba08-18f8e2461abe

Denojean-Mairet, M., López-Pernas, S., Agbo, F. J., & Tedre, M. (2024). A literature review on the integration of microlearning and social media. *Smart Learning Environments, 11*(1), Article 46. https://doi.org/10.1186/s40561-024-00334-5 Springer Link

Faccia, A., Ridon, M., Beebeejaun, Z., & Moşteanu, N. R. (2023). Advancements and challenges of generative AI in higher educational content creation: A technical perspective. In *Proceedings of the 2023 8th International Conference on Information Systems Engineering (ICISE '23).* https://doi.org/10.1145/3641032.3641055

Fadli, H. (2025). AI-enabled microlearning and case study atomisation: ICT pathways for inclusive and sustainable higher education. *Sustainability, 17*, 11012. https://doi.org/10.3390/su172411012

Ferrari, R. (2015). Writing narrative style literature reviews. *Medical Writing, 24*(4), 230–235. https://www.researchgate.net/publication/288039333_Writing_narrative_style_literature_reviews

Ferreira, E., Quincozes, S. E., Ciocca, M. M., Silva, G., Souza, T., & da Costa, S. R. (2025). How the Educator 5.0 Will Not Be Replaced by AI: An Adaptive Microlearning Architecture Based on Augmented Intelligence. In *Simpósio Brasileiro de Informática na Educação (SBIE 2025).* https://doi.org/10.5753/sbie.2025.12439

Forsström, S., & Sagersten, C. (2024). Teaching the use of generative AI tools to working professionals: A microlearning approach. In *ICERI2024 Proceedings* (pp. 21–28). https://doi.org/10.21125/iceri.2024.0027 IATED Digital Library

Giraldo Pérez, B. (2022). *A generic approach to microlearning objects (microLOs) from the perspective of terminological principles and methods* (Doctoral dissertation). https://utheses.univie.ac.at/detail/63927

Giurgiu, L. (2017). Microlearning: An evolving elearning trend. *Scientific Bulletin, 22*(1), 18-23. https://doi.org/10.1515/bsaft-2017-0003

Greenhalgh, T., Thorne, S., & Malterud, K. (2018). Time to challenge the spurious hierarchy of systematic over narrative reviews? *European Journal of Clinical Investigation, 48*(6), e12931. https://doi.org/10.1111/eci.12931

Holmes, W., Bialik, M., & Fadel, C. (2023). *Artificial intelligence in education: Promises and implications for teaching and learning* (2nd ed.). Center for Curriculum Redesign. https://www.researchgate.net/publication/332180327_Artificial_Intelligence_in_Education_Promise_and_Implications_for_Teaching_and_Learning

Hug, T. (2022). Microlearning formats in crisis? Theses in the field of tension between corona-induced short-term solutions, apodictic rhetoric's of no alternatives and perspectives open to the future. In T. Hug, M. Lindner, & P. A. Bruck (Eds.), *Microlearning: Emerging research and opportunities* (pp. 125-139). Springer International Publishing. https://doi.org/10.1007/978-3-031-13359-6_8

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., Weller, J., Kuhn, J., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kohnke, L. (2025). Empowering pre-service teachers with generative artificial intelligence and microlearning pathways to self-directed growth. *Asian Journal of Applied Linguistics, 8*(4), 102889. https://doi.org/10.29140/ajal.v8n4.102889

Kravchenko, V., & Cherninskyi, A. (2025). *Microlearning in mobile applications: Neurobiological foundations, design challenges, and future directions for cognitive optimization*. SSRN. https://doi.org/10.2139/ssrn.5563833 & https://papers.ssrn.com/sol3/papers.cfm?abstract_id=5563833

Leong, K., Sung, A., Au, D., & Blanchard, C. (2021). A review of the trend of microlearning. *Journal of Work-Applied Management, 13*(1), 88-102. https://doi.org/10.1108/JWAM-10-2020-0044

Mattei, V. (2025). *Development of an AI-enhanced microlearning platform for enterprise knowledge transfer* (Master's thesis). Politecnico di Torino. https://webthesis.biblio.polito.it/secure/36413/1/tesi.pdf

McKee, C., & Ntokos, K. (2022). Online microlearning and student engagement in computer games higher education. *Research in Learning Technology, 30*, 2680. https://doi.org/10.25304/rlt.v30.2680

Mohammed, G. S., Wakil, K., & Nawroly, S. S. (2018). The effectiveness of microlearning to improve students' learning ability. *International Journal of Educational Research Review, 3*(3), 32-38. https://doi.org/10.24331/ijere.415824

Monib, W. K., Qazi, A., Apong, R. A., & Mahmud, M. (2024). Investigating learners' perceptions of microlearning: Factors influencing learning outcomes and engagement in higher education. *IEEE Access, 12*, 167610–167634. https://doi.org/10.1109/ACCESS.2024.3472113

Monib, W. K., Qazi, A., Apong, R. A., Santos, J. H., & Mahmud, M. (2025). The MIND model: A microlearning AI-integrated instructional design for enhanced learning outcomes. *Scientific Reports, 15*(1). https://doi.org/10.1038/s41598-025-24910-y Nature

Moore, P. D. (2025). Smarter learning: Integrating AI into instructional design for 21st-century education. *Scientia Moralitas International Journal of Multidisciplinary Research, 10*(1), 86–108. https://doi.org/10.5281/zenodo.16335328 David Publisher

Noverisa, E. J., Hakim, R. F., & Rahayu, P. (2025). AI-assisted design of microlearning media for basic Japanese grammar. *Jurnal Bébasan, 12*(1), 22–29. https://doi.org/10.26499/bebasan.v12i1.274

Ojochegbe, A. T. (2025). Tiny steps, giant leaps: The place of micro-learning in language and literature. *Journal of World Science, 4*(1), 94–103. https://doi.org/10.58344/jws.v4i1.1277 Riviera Publishing

Pal, A. (2025). Inclusive & equitable learning design: Integrating systems thinking and action research in generative AI-driven educational content. *Journal of Applied Instructional Design, 14*(2). https://doi.org/10.59668/2222.21482 & https://edtechbooks.s3.us-west-2.amazonaws.com/pdfs/2222/21482.pdf

Paunovic, N. (2025). *Exploring LLM capabilities to create content for microlearning* (Bachelor's thesis). Stockholm University. https://www.diva-portal.org/smash/get/diva2:1972768/FULLTEXT01.pdf

Reynolds, J., & Dolasinski, M. J. (2024). Applications of microlearning tools and platforms. *ICHRIE Research Reports, 9*(5), Article 1. https://doi.org/10.61701/649092.995 Digital Commons@DePaul

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education, 26*(2), 582-599. https://doi.org/10.1007/s40593-016-0110-3

Saha, S., Rahbari, F., Sadique, F., Velamakanni, S. K. C., Farooque, M., & Rothwell, W. J. (2025). Next-gen education: Enhancing AI for microlearning. In *Proceedings of the 2025 ASEE Annual Conference & Exposition*. American Society for Engineering Education. https://peer.asee.org/next-gen-education-enhancing-ai-for-microlearning

Stavrinou, L., Constantinides, A., Belk, M., & Vassiliou, V., Liarokapis, F., Constantinides, M. (2025). The Reel Deal: Designing and Evaluating LLM-Generated Short-Form Educational Videos. In CHIGreece 2025: 3rd International Conference of the ACM Greek SIGCHI Chapter (CHIGreece 2025), September 24–26, 2025, Hermoupolis, Syros, Greece. ACM, New York, NY, USA, 9 pages. https://doi.org/10.1145/3749012.3749048

Sullivan, M., Kelly, A., & McLaughlan, P. (2023). ChatGPT in higher education: Considerations for academic integrity and student learning. *Journal of Applied Learning and Teaching, 6*(1), 1-10. https://doi.org/10.37074/jalt.2023.6.1.17

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Ullmann, T. D., Edwards, C., Bektik, D., Herodotou, C., & Whitelock, D. (2024). Towards generative AI for course content production. *European Journal of Open, Distance and E-Learning, 27*(2), 240–259. https://doi.org/10.2478/eurodl-2024-0013

Velamakanni, S. K. C., & Saha, S. (2025). Snackable study: Boosting micro-learning with bite-size videos. In *Proceedings of the 2025 ASEE Annual Conference & Exposition*. https://doi.org/10.18260/1-2--57656

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education—Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), Article 39. https://doi.org/10.1186/s41239-019-0171-0

Zulfa, A. Z., Azzahra, N. A., Nurjali, Nisak, S. K., & Yatima, K. (2024). Learning Transformation: AI Trends, Microlearning, and Gamification. *International Journal of Education Science and Culture, 1*(3), 9–15. https://ejournal.almusthofa.org/index.php/IJESC/article/view/145/71

Appendix: List of Reviewed Articles

No.	Author (s)	Year	Title	Journal/Source
1	Faccia, A., Ridon, M., Beebeejaun, Z., & Moşteanu, N. R.	2023	Advancements and challenges of generative AI in higher educational content creation: A technical perspective	*Proceedings of the 2023 8th International Conference on Information Systems Engineering (ICISE '23)*
2	Choi, G. W., Kim, S. H., Lee, D., & Moon, J.	2024	Utilizing Generative AI for instructional design: Exploring strengths, weaknesses, opportunities, and threats	*TechTrends*
3	Forsström, S., & Sagersten, C.	2024	Teaching the use of generative AI tools to working professionals: A microlearning approach	*ICERI2024 Proceedings*
4	Monib, W. K., Qazi, A., Apong, R. A., & Mahmud, M.	2024	Investigating learners' perceptions of microlearning: Factors influencing learning	*IEEE Access*

No.	Author (s)	Year	Title	Journal/Source
			outcomes and engagement in higher education	
5	Reynolds, J., & Dolasinski, M. J.	2024	Applications of microlearning tools and platforms	*ICHRIE Research Reports*
6	Ullmann, T. D., Edwards, C., Bektik, D., Herodotou, C., & Whitelock, D.	2024	Towards generative AI for course content production	*European Journal of Open, Distance and E-Learning*
7	Zulfa, A. Z., Azzahra, N. A., Nurjali, Nisak, S. K., & Yatima, K.	2024	Learning Transformation: AI Trends, Microlearning, and Gamification	*International Journal of Education Science and Culture*
8	Ferreira, E., Quincozes, S. E., Ciocca, M. M., Silva, G., Souza, T., & da Costa, S. R.	2025	How the Educator 5.0 Will Not Be Replaced by AI: An Adaptive Microlearning Architecture Based on Augmented Intelligence	*Simpósio Brasileiro de Informática na Educação (SBIE 2025)*
9	Kohnke, L.	2025	Empowering pre-service teachers with generative artificial intelligence and microlearning pathways to self-directed growth	*Asian Journal of Applied Linguistics*
10	Kravchenko, V., & Cherninskyi, A.	2025	*Microlearning in mobile applications: Neurobiological foundations, design challenges, and future directions for cognitive optimization*	SSRN (Social Science Research Network)

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No.	Author (s)	Year	Title	Journal/Source
11	Mattei, M.	2025	*Development of an AI-enhanced microlearning platform for enterprise knowledge transfer*	Master's thesis, Politecnico di Torino
12	Monib, W. K., Qazi, A., Apong, R. A., & Mahmud, M.	2025	The MIND model: A microlearning AI-integrated instructional design for enhanced learning outcomes	*Scientific Reports*
13	Moore, P. D.	2025	Smarter learning: Integrating AI into instructional design for 21st-century education	*Scientia Moralitas International Journal of Multidisciplinary Research*
14	Noverisa, E. J., Hakim, R. F., & Rahayu, P.	2025	AI-assisted design of microlearning media for basic Japanese grammar	*Jurnal Bébasan*
15	Ojochegbe, A. T.	2025	Tiny steps, giant leaps: The place of micro-learning in language and literature	*Journal of World Science*
16	Pal, A.	2025	Inclusive & equitable learning design: Integrating systems thinking and action research in generative AI-driven educational content	*Journal of Applied Instructional Design*
17	Paunovic, N.	2025	*Exploring LLM capabilities to create content for microlearning*	Bachelor's thesis, Stockholm University
18	Saha, S., Rahbari, F., Sadique, F., Velamakanni, S. K. C., Farooque, M., & Rothwell, W. J.	2025	Next-gen education: Enhancing AI for microlearning	*Proceedings of the 2025 ASEE Annual Conference & Exposition*

No.	Author (s)	Year	Title	Journal/Source
19	Stavrinou, L., Constantinides, A., Belk, M., & Vassiliou, V., Liarokapis, F., Constantinides, M.	2025	The Reel Deal: Designing and Evaluating LLM-Generated Short-Form Educational Videos	In CHIGreece 2025: 3rd International Conference of the ACM Greek SIGCHI Chapter (CHIGreece 2025)
20	Velamakanni, S. K. C., & Saha, S.	2025	Snackable study: Boosting micro-learning with bite-size videos	*Proceedings of the 2025 ASEE Annual Conference & Exposition*