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Impact of AI-assisted microlearning on student engagement in an online environment in higher education

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Introduction: The rapid advancement of technology has transformed teaching and learning in educational settings, introducing innovative tools into teacher education programs. Microlearning integration in the educational process is significantly influenced by the emergence of generative artificial intelligence (AI) tools. This article investigates the impact of the integration of AI-based microlearning on the learning engagement of college students in a multimedia course within the educational technology department. Investigating engagement is essential as it influences students' motivation, academic performance, and perceptions. Yet, research on AI-assisted microlearning remains limited, particularly in the Middle East, underscoring the need for further investigation.
Methods: Using an explanatory sequential mixed-methods approach, the study involved 50 students enrolled in an educational technology course. A quasi-experimental design was implemented and supplemented with a phenomenological approach. Data were collected from both experimental and control groups, along with online forum discussions and 25 semi-structured interviews with pre-service teachers who participated in AI-assisted microlearning.
Results: ANCOVA analysis revealed that AI-assisted microlearning positively influenced student engagement and its components. Through inductiveand deductive content analysis four main themes emerged, including cognitive, emotional, social, and behavioral engagement, further divided into six subthemes: grabbing attention, personalized learning, reduced frustration, task completion, sharing, and competition.
Discussion: The findings highlight the role of empowering educators through the integration of technology, equity, and innovation in higher education. AI-assisted microlearning serves as a pedagogical tool to foster inclusive, adaptive, and engaging learning environments. Recommendations include using AI to tailor content to individual learning styles, thereby supporting educators in delivering equitable and innovative educational experiences.

KEYWORDS
AI, AI-based learning, cognitive engagement, engagement, microlearning

1 Introduction

Recently, the rise of digitalization has reshaped how knowledge is acquired, necessitating a shift from conventional teaching approaches. Modern education must now prioritize fostering students' digital competencies, including critical analysis, creative thinking, and flexibility (Díaz-Garcia et al., 2022). To align with technological demands and advance the sustainable development goals (SDGs), it is essential to integrate adaptive strategies that support growth and achievement in the digital age (Silva et al., 2025).

Microlearning has created new opportunities in teaching–learning process. Educators should leverage the advantages of this advancing technology. With its features that lean toward shorter, concise multimedia presentations (Alias and Razak, 2024; Cruz et al., 2022). Microlearning integrates advanced digital technologies into the teaching–learning process and transforms teacher and student roles by offering more opportunities with active, participatory, and meaningful learning (Choudhary, 2024; Yogeswari et al., 2022). Alongside this promising technology, generative AI has emerged, making the two technologies a great option for AI-assisted microlearning (Boumalek et al., 2024). Microlearning or micro-content, defines how structured knowledge is delivered in several short, well-defined, and interconnected sessions (Javorcik et al., 2023). Micro-content breaks the instructional material into small units and shorter learning activities to provide quick knowledge focused on a single topic. In microlearning, videos, tutorials, resources, and tips are designed in such a clear and comprehensible way so they can be consumed in a short time, with an increased number of feedback cycles (Choudhary and Pandita, 2024). Microlearning and generative AI offer a great chance to revolutionize the student learning experience. By integrating generative AI with microlearning, a simple content delivery tool can transform learning experience to an adaptive, customized environment that is designed around learner's needs and preferences (Rüdian and Pinkwart, 2023). AI-assisted microlearning represents an evolutionary advancement of this approach, integrating AI technologies to create adaptive, personalized, and dynamically generated learning experiences. Unlike traditional microlearning's static content delivery, AI-assisted microlearning employs algorithms that analyze individual learner data—including performance patterns, engagement metrics, and preference indicators—to generate or modify content in real-time (Rüdian and Pinkwart, 2023). This system creates a feedback loop where the learning content evolves based on learner interaction, effectively creating personalized learning pathways for each student.

Furthermore, AI-assisted microlearning supports the broader imperative of empowering educators in higher education by integrating technology, equity, and innovation into teaching practices (Fadli, 2025). By delivering content in accessible, bite-sized formats, microlearning reduces cognitive load and accommodates diverse learning paces and styles, thereby promoting equitable learning opportunities (Zhang and West, 2020). This approach enables educators to leverage technology not merely as a tool for content delivery, but as a means to foster inclusive and adaptive learning environments that cater to varied student needs (McNeill and Fitch, 2022). Additionally, the integration of generative AI with microlearning encourages pedagogical innovation, allowing educators to design personalized, scalable, and engaging learning experiences that align with contemporary educational demands (Ruiz-Rojas et al., 2023). Thus, microlearning serves as a catalyst for transforming traditional teaching paradigms, empowering educators to implement student-centered, technology-enhanced strategies that advance both educational quality and equity in higher education.

AI-based content generation and distribution boost participation and comprehension of students (Busse et al., 2020). This student-centered approach takes the focus away from teachers and places students at the center of their learning (Wang et al., 2025). Generative AI-powered microlearning allows learners to study flexibly, providing adaptive instructional content at learner's own pace, customized to their interests with the support of AI (Mogavi et al., 2024), along with practice and interactive activities to reinforce learning (Al-Nasheri and Alhalafawy, 2023; Choudhary and Pandita, 2024). The objectives of this contribution will be as follows: to compare engagement levels between students experiencing AI-assisted microlearning and those receiving traditional online instruction. Also, to identify which engagement dimensions (cognitive, emotional, behavioral, social) are most significantly affected by AI-assisted microlearning. Moreover, to explicate the mechanisms through which AI-assisted microlearning influences engagement patterns.

Hence, this study addresses three research questions:

1. Does AI-assisted microlearning in an online environment affect student engagement and its dimensions?
2. What types of engagement occur in AI-assisted microlearning in online learning?
3. How does AI-assisted microlearning influence engagement in an online environment?

2 Literature review

2.1 Microlearning

Microlearning has emerged as a prominent instructional strategy, delivering content in concise, focused segments that match with contemporary preferences for brief, accessible learning (Kossen and Ooi, 2021). This approach empowers learners by offering flexibility in when and what they learn, effectively supporting self-directed education (Judijanto, 2025). Its formats have diversified beyond text to include short videos, interactive simulations, podcasts, and gamified elements—all designed to reduce cognitive load and enhance engagement (Al-Nasheri and Alhalafawy, 2023; McNeill and Fitch, 2022). Moreover, microlearning facilitates just-in-time learning and has demonstrated effectiveness across varied contexts such as corporate training, healthcare education, and language learning (Zhang and West, 2020; Silva et al., 2025; Skalka et al., 2021). However, traditional implementations often rely on static, non-adaptive content, which limits personalization and fails to address individual learner needs (Richardson et al., 2023). Richardson et al. (2023) investigated microlearning's flexibility and reported that it enables learners to access relevant information on demand by eliminating the need for extended formal sessions. Supporting this, Alias and Razak (2025) demonstrated multiple benefits of microlearning techniques, such as enhancing learning outcomes and improving knowledge acquisition. Silva et al. (2025) conducted a systematic review examining microlearning delivered in brief modules, revealing its effectiveness in enhancing knowledge retention and linking concepts to practical applications. Similarly, Judijanto (2025) performed a bibliometric analysis exploring microlearning's role in a lifelong learning, concluding that it significantly supports self-directed education. Research has demonstrated microlearning's effectiveness in various contexts including corporate training (Zhang and West, 2020), healthcare education (Silva et al., 2025), and language learning (Skalka et al., 2021).

The proliferation of mobile devices has further facilitated just-in-time learning opportunities, with studies showing improved knowledge retention when content is accessible via smartphones (Nikkhoo et al., 2023).

Despite these advancements, traditional microlearning approaches often rely on static, predetermined content modules that lack adaptability to individual learner needs. This one-size-fits-all limitation reduces the potential for truly personalized learning experiences (Monib et al., 2024).

2.2 Generative AI in education: from automation to personalization

Generative AI represents a paradigm shift in educational technology, moving beyond content delivery systems to become dynamic content creation partners. Unlike previous educational technologies that primarily organized or presented existing content, generative AI systems create original educational materials—including text explanations, assessment items, visual aids, and interactive simulations—based on pedagogical parameters and learner data (Díaz Redondo et al., 2021).

Generations of AI in education applications include content generation. Studies examine AI's ability to create customized learning materials at scale (Mogavi et al., 2024). Assessment is another application of generative AI, with research exploring AI-generated formative assessments and automated feedback systems (Rüdian and Pinkwart, 2023).

While research on generative AI in education is expanding, most studies focus on content creation capabilities rather than examining how AI integration transforms specific pedagogical approaches or affects multidimensional learning outcomes.

2.3 Generative AI-assisted microlearning

Generative AI is revolutionizing education, driving innovation in areas such as text, image, audio, and video generation (Díaz Redondo et al., 2021). Microlearning plays a crucial role in developing individualized educational experiences. By evaluating learner data, generative AI produces customized content that aligns with individual skill levels and preferences, boosting engagement and retention. It also facilitates dynamic learning pathways that evolve with student progress, optimizing educational results (Mogavi et al., 2024). Additionally, generative AI enhances efficiency in content creation, allowing scalable and creative solutions for educators. Its potential to inspire new teaching methodologies enables more interactive and immersive learning experiences (Slivnaya et al., 2023). As technology evolves, generative AI is poised to redefine education, helping educators address diverse learning needs while fostering a more effective and engaging academic environment (Ruiz-rojas et al., 2023).

The intersection of microlearning, micro-content, and generative AI marks a significant shift in modern education. Microlearning's concise, targeted format has proven effectiveness in knowledge delivery and construction (Ruiz-Rojas et al., 2023), yet manually tailoring micro-content to individual learners poses scalability challenges. Generative AI addresses this by using deep learning to analyze learner data, preferences, behaviors, and performance, which enables the automated production of personalized microlearning materials (Mahendra and Killis, 2025). This ensures content is precisely adapted to each student's needs and learning styles (Lee, 2023). Furthermore, generative AI continuously improves through iterative learning, staying responsive to educational advancements. By integrating generative AI, microlearning becomes more scalable, customizable, and adaptive, ultimately enhancing student engagement and academic success (Kohnke, 2023; Cao et al., 2025; Díaz Redondo et al., 2021).

2.4 Engagement and microlearning

Learner engagement is a multifaceted construct encompassing behavioral, emotional, and cognitive aspects (Shi et al., 2023). As a critical factor in the learning process, engagement significantly influences students' learning (Guan et al., 2023; McKee and Ntokos, 2022). Behavioral engagement refers to observable actions and task participation (Draxler et al., 2022; Guan et al., 2023; Wong et al., 2024), while emotional engagement represents internal states that are not directly observable (Fredricks et al., 2016; Guan et al., 2023; Shi et al., 2023; Zhang and West, 2020). Emotional engagement relates to students' affective responses, which positively impact achievement (Shi et al., 2023; Yin et al., 2021; Wang and Degol, 2014). Cognitive engagement reflects deep cognitive strategies that shape knowledge processing, retention, and application, ultimately strengthening problem-solving skills (Shi et al., 2023). When applied to microlearning design, these engagement frameworks enable educational content to adapt to individual learning preferences while fostering active participation and sustained involvement (Busse et al., 2020; Sahin and Kırmızıgül, 2023). However, few studies have examined how AI-assisted microlearning influences engagement. Previous studies investigated the influence of microlearning on engagement. A study conducted by McKee and Ntokos (2022) examined how microlearning affects online student engagement. Results showed that microlearning helps students to stay entirely focused and engaged more in learning by allowing them to complete instructional tasks depending on their own schedule rather than on someone else's schedule. In contrast, Moore et al. (2024) argued that microlearning enhances students' engagement and motivation, these two factors that are crucial for sustaining lifelong learning behaviors.

From reviewing the literature, it is evident that few studies have investigated how AI-based microlearning affects engagement. Moreover, this study novelty lies in the crucial and new topic it explores. Also, this study is unique compared to other studies as it utilizes experimental and qualitative design compared to other previous studies. Despite the growing body of research about microlearning, there remains a lack of clarity regarding the current state of the literature related to influence of AI-based microlearning on engagement in online environment.

2.4.1 Theoretical engagement framework

In this research, Bowden engagement theory is adopted. The Bowden framework of engagement is a strategic model designed to enhance engagement and loyalty by focusing on key touchpoints in the education process. It emphasizes four aspects: cognitive engagement, which is related to cognition, understanding, and critical thinking. Emotional engagement, which focuses on connection, value creation, and long-term relationship building. Behavioral engagement, which is defined as observable actions and participation in learning activities, reflecting effort, persistence, and adherence to academic tasks. Social engagement, which includes learners' interactions with peers, instructors, or AI agents to build relationships, share knowledge, and collaborate (Bowden and Tickle, 2021). The intersection of the Bowden engagement theory is selected as a framework for this study as it emphasizes on four dimensions like emotional connection, information exchange, and continuous interaction, principles that align seamlessly with microlearning (bite-sized, focused learning experiences). Bowden's engagement framework (Bowden and Tickle, 2021) also provides a multidimensional lens through which to examine the impact of AI-assisted microlearning. This study aligns Bowden's four engagement dimensions, cognitive, emotional, behavioral, and social with the affordances of AI-driven microlearning. For example, AI personalizes micro-content to match learners' knowledge levels by reducing cognitive load and enhancing critical thinking through adaptive challenges. Moreover, AI reduces frustration by delivering bite-sized, manageable content and providing positive reinforcement. AI promotes task completion and persistence through interactive modules, instant feedback, and gamified elements. AI-facilitated forums and peer interactions encourage knowledge sharing and collaborative learning.

While substantial literature exists on microlearning, generative AI in education, and student engagement as separate domains, minimal research examines their intersection. Specifically, three interconnected knowledge gaps necessitate investigation. First, the AI-microlearning integration gap. Previous studies have examined microlearning effectiveness (McKee and Ntokos, 2022) or AI applications in education (Mogavi et al., 2024) as separate phenomena. The synergistic potential of combining these approaches, where AI not only delivers but dynamically generates personalized micro-content remains underexplored. Second, the multidimensional engagement gap: most technology-focused engagement studies emphasize behavioral metrics (login frequency, completion rates) while neglecting how technological interventions affect cognitive, emotional, and social engagement dimensions in an integrated manner.

Third, the contextual application gap. Limited research examines these phenomena in Middle Eastern higher education contexts, where cultural, linguistic, and infrastructural factors may mediate technology adoption and effectiveness.

This study's novel contribution lies in addressing these gaps through three distinctive contributions. First, conceptual innovation: by investigating AI-assisted microlearning as a unified pedagogical approach rather than separate technologies, this study advances understanding of how AI transforms microlearning from a content delivery method to an adaptive learning system. Second, methodological integration: by employing a mixed-methods design that combines quasi-experimental comparison with phenomenological exploration, the study allows for both quantification of effects and deep understanding of engagement experiences. Third, contextual specificity: by focusing on Palestinian higher education, the study addresses regional underrepresentation in educational technology research while providing insights potentially transferable to similar developing educational contexts. Uniquely, this study extends Bowden's engagement framework by examining how AI-mediated personalization mechanisms differentially affect cognitive, emotional, behavioral, and social engagement dimensions. This addresses calls for research that moves beyond "whether" technology affects engagement to examine "how" and "why" specific technological features influence different engagement components (Wang et al., 2025).

3 Methodology

3.1 Research design

The impact of using AI-assisted microlearning is investigated by a mixed method design; by both quantitative and qualitative approaches. An explanatory sequential design (Creswell and John, 2018) was employed. The design was chosen to quantify the impact of AI-assisted microlearning on student engagement, and to explore the lived experiences and contextual factors influencing engagement through qualitative insights.

This study utilized a quasi-experimental design and a phenomenology approach, where participants went through the experience of using AI-assisted microlearning and expressed their thoughts and perspectives. Both groups completed the pre-test of engagement scale. During 10 weeks of multimedia course, both groups followed the same sequence of participating in attending online class activities. During the period, students in both groups followed the sequence three times a week, resulting in a total of 42 online classes 50-min sessions. Several topics were taught, including multimedia components, multimedia significance, designs of using multimedia in teaching technology curriculum, and theories of design. All students completed the pre-test and post-test. The experimental group additionally participated in discussion forums and semi-structured interviews 1 week after the last session, as shown in Figure 1.

3.2 Participants

Students at the third-year and fourth-year study levels at Palestine Technical University–Kadoorie (PTUK) in a multimedia course from technology education department formed the sample for this study. They were enrolled in M*ultimedia in Educational Technology* at PTUK during the fall semester of the 2025/2026 academic year. Selection criteria included: enrollment in the designated course section, completion of prerequisite courses in computer literacy and instructional design, no prior formal training in AI-assisted learning tools or microlearning platforms, and willingness to participate in online forums and optional interviews for qualitative data. Students were pre-service teachers preparing to teach technology curricula in schools. Technology education students who enrolled in this program itself aims to gain a deep understanding of current teaching strategies and theories to teach technology curriculum in schools. Technology education study program aims to strengthen technical skills, as well as to enhance designing, and production of educational technology products. Quasi experiment consisted of 50 students who were purposively selected from the same course taught by one instructor to minimize instructor-style effects. Purposive sampling was applied since a quasi-experiment was conducted (Salhab, 2024). Table 1 shows the demographic data of the respondents.

A power analysis was conducted using G*Power 3.1 (Faul et al., 2009) for a mixed-design ANCOVA with two groups, one covariate (pre-test score), and four engagement dimensions. With an assumed medium effect size ($f = 0.25$), $\alpha = 0.05$, and power = 0.80, the recommended sample size was 44. A sample of 50 was selected to account for potential attrition and to ensure robust qualitative data from at least 20 interview participants (experimental group).

Since the sample was drawn from a single university, discipline (technology education), and cultural context (Palestine), findings may be limited in generalizability of findings to other populations, disciplines, or regions. Future multi-site and cross-disciplinary replications are recommended.

To mitigate internal validity threats, stratified random assignment was conducted based on academic year and prior GPA, and pre-test equivalence was checked via t-tests. Equivalency in pre-test scores was confirmed, as shown in Table 2. Another threat, which included history and maturation, was mitigated by making control group exposed to same timeline and external events and ANCOVA controlled for pre-test scores.

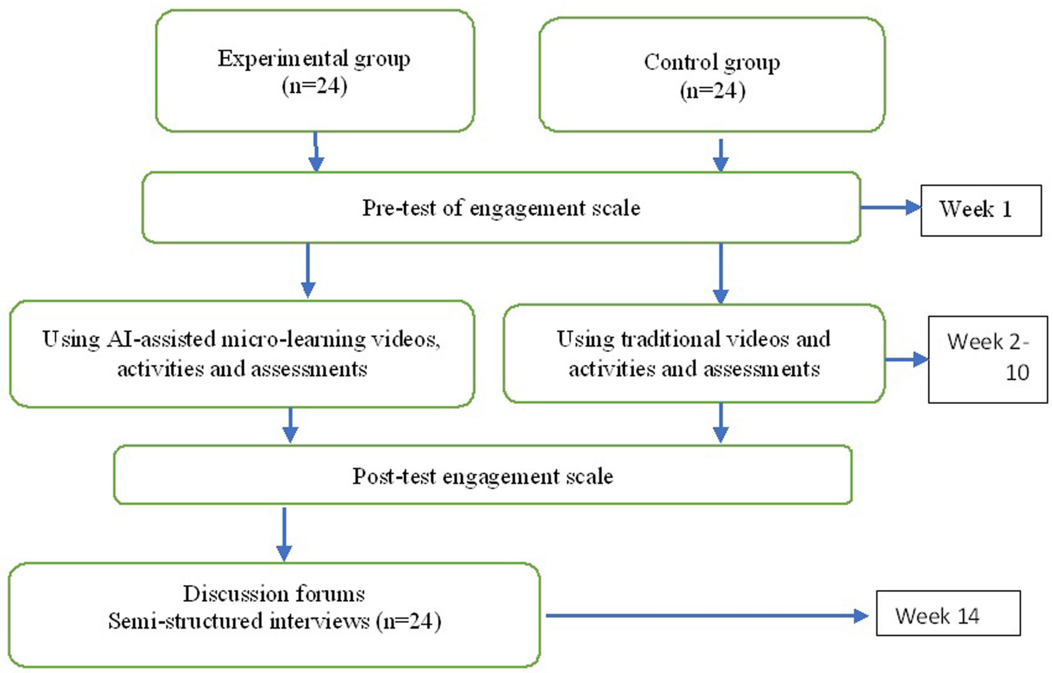

FIGURE 1
Flowchart of the explanatory sequential mixed-methods research design, illustrating participant groups, intervention, and data collection phases.

TABLE 1 Sample demographic.

Characteristic	Experimental (n = 25)	Control (n = 25)	Total (N = 50)
Gender			
Male	12 (48%)	11 (44%)	23 (46%)
Female	13 (52%)	14 (56%)	27 (54%)
Academic year			
Third year	14 (56%)	13 (52%)	27 (54%)
Fourth year	11 (44%)	12 (48%)	23 (46%)
Prior GPA (Mean ± SD)	3.42 ± 0.31	3.38 ± 0.29	3.40 ± 0.30
Prior AI experience			
Yes (informal use)	17 (68%)	16 (64%)	33 (66%)
No	8 (32%)	9 (36%)	17 (34%)
Device access			
Smartphone only	4 (16%)	5 (20%)	9 (18%)
Laptop + smartphone	21 (84%)	20 (80%)	41 (82%)

Group equivalence at baseline.
To ensure that the experimental and control groups were comparable before the intervention, independent samples t-tests were conducted on pre-test engagement scores and prior GPA. Chi-square tests were used for categorical variables (gender, academic year, prior AI experience). Results confirmed no significant differences between groups at baseline (all *p* > 0.05).

TABLE 2 Baseline equivalence tests.

Variable	Experimental (M/SD or %)	Control (M/SD or %)	Test statistic	p-value
Pre-test engagement	3.21 ± 0.45	3.18 ± 0.43	$t(48) = 0.24$	0.812
Prior GPA	3.42 ± 0.31	3.38 ± 0.29	$t(48) = 0.48$	0.634
Gender (Male)	48%	44%	$\chi^2(1) = 0.08$	0.777
Academic year (Third)	56%	52%	$\chi^2(1) = 0.08$	0.777
AI experience (Yes)	68%	64%	$\chi^2(1) = 0.10$	0.752

Two groups of students ($N = 50$) were assigned to one of two conditions, the experimental group ($n = 25$), who received AI-assisted microlearning modules, and a control group ($n = 25$) who received traditional online learning materials without AI personalization. A stratified random assignment was used within the purposively sampled cohort. Students were first stratified by academic year (third vs. fourth year) and prior GPA (above/below cohort median) to ensure balanced groups. Within each group, students were randomly assigned to either the experimental or control group using a random number generator. Participants were not informed of their group designation to reduce expectancy effects. They were told the study was investigating modern digital learning tools.

The same instructor taught both groups to control for teaching style, communication, and content delivery differences. The instructor's role was standardized by providing identical weekly topics, objectives, and assignment deadlines to both groups. The instructor also participated in discussion forums with a standardized weekly presence and used a scripted set of discussion prompts to ensure consistency. To minimize bias, the instructor was not involved in data collection, analysis, or interpretation. A teaching assistant managed the AI tool integration and microlearning delivery for the experimental group to prevent differential treatment.

For discussion forums and semi structured interviews, 12 participants from third year students from the College of Arts and Social Sciences in Technology Education department at PTUK who were in the experimental group participated in the study. The selection criteria were based on knowledge and experience of participants who fluently uses online platforms and participants who passed the basic course of computer courses. Purposive sampling was used to select participants from the same course and instructor to control for instructor effect. Participants were randomly assigned to experimental or control groups.

3.3 Research context

This study was conducted for a multimedia course at PTUK in northern Palestine. It had six goals, including: identifying multimedia concept and components, designing an educational poster and a brochure about a lesson in technology school curriculum, creating educational videos about lessons in technology curriculum, and utilizing AI tools to design images and edit images. In addition, the course incorporated short content-videos, discussion, forum, and assignments. The AI tools used by faculty are listed in Table 3.

3.4 Data collection tools

The study followed an explanatory sequential design, with data collection conducted in three sequential stages, as outlined by Bowen (2017). This approach involves first gathering and analyzing quantitative data, followed by qualitative data collection discussion forums and semi-structured interviews. This design aims to quantifying the phenomenon under investigation and then explore the findings in greater depth through qualitative insights.

3.5 Pre- and post-intervention scales

As part of the quasi-experimental design, 50 students completed a pre-course engagement scale before the intervention (AI-assisted microlearning). Both the control and experimental groups completed the survey online, which offered a convenient, time-efficient, and cost-effective method for data collection (Herrmann-Abell et al., 2016). The pre-existing scale, originally designed to assess engagement toward Information and Communication Technology (ICT) (Creswell and Clarck, 2011), was adapted for micro learning. The scale comprised 20 items across three constructs: the cognitive dimension consisted of 7 items, the affective dimension was composed of 8 items, and the behavioral dimension consisted of 5 items. All items were measured on a 5-point Likert scale (1 = completely disagree, 5 = entirely agree).

3.6 Validation and reliability

Since the scale was translated from English to Arabic, its validity was assessed through expert review (face validity) by professors specializing in educational psychology, educational technology, and curriculum design. Pearson's correlation was used to verify construct validity, with coefficients ranging between 0.621–0.882 for affective, 0.631–0.811 for behavioral, and 0.677–0.834 for cognitive dimensions—all statistically significant ($p < 0.01$), confirming strong validity (Rebouças et al., 2018).

Reliability was tested using Cronbach's alpha, yielding high internal consistency: 0.868 (affective), 0.754 (behavioral), and 0.736 (cognitive), with an overall scale reliability of 0.834, indicating robust consistency (Oktavia et al., 2018).

TABLE 3 AI tools used and their pedagogical functions.

AI tool used	Pedagogical function	Example use in the study
ChatGPT	Generating personalized quizzes, providing instant feedback, answering student queries.	Used to create short quizzes after microlearning videos to reinforce concepts and assess understanding.
Canva AI	Designing engaging and personalized video content, infographics, and visual aids.	Employed to produce bite-sized instructional videos and infographics tailored to course topics (e.g., image editing, multimedia design).
AI-powered leaderboards	Fostering competition and motivation through gamification.	Implemented to rank students based on quiz scores and module completion, encouraging participation and task completion.
Adaptive learning algorithms	Personalizing content delivery based on learner performance and preferences.	Adjusted difficulty and recommended resources dynamically based on quiz results and interaction patterns.
Virtual assistants/chatbots	Facilitating learner–interface interaction and reducing cognitive load.	Provided just-in-time support during microlearning activities, answering procedural and content-related questions.

3.7 Semi structured interviews

Qualitative data were collected through semi-structured interviews. After AI-assisted microlearning intervention, 25 interviews were conducted with participants who voluntarily decided to participate. These participants met two criteria: (a) third-year college level or higher, and (b) enrollment in the multimedia course in 2025/2026. Sessions lasted 30–45 min, conducted via Zoom and in-person, with participant consent for recording. Data were also collected from 25 students' forum comments in a multimedia course at PTUK, anonymized to protect identities. Semi-structured interviews included the following questions:

- What do you think about using AI-based microlearning content in a multimedia course?
- Describe your overall engagement experience when using AI-assisted microlearning in this course.
- Describe your feelings when you were using AI-assisted microlearning in this course.
- Tell us about your participation in online class activities while using AI-assisted microlearning in this course.
- Tell me your social interactions when utilizing AI-assisted microlearning during your class.

4 Data analysis

> *RQ1.* Does AI-assisted microlearning in online environment affect student engagement and its dimensions?

An ANCOVA (one way analysis of covariance) test was conducted to calculate the difference in engagement scores between the two groups control groups. To determine whether there was a significant difference in the means of engagement scores, an independent *t*-test was used. Assumptions for ANCOVA were assessed. These assumptions included normality (as shown in Table 3) and regression of slopes (as shown in Table 3) (Dimitrov and Rumrill, 2003; Garfield and Ben-Zvi, 2007). To determine whether the data were normally distributed, Shapiro–Wilk was conducted. The *p*-values were calculated and indicated values greater than 0.05 for overall engagement and its domains, as shown in Table 4.

Table 4 shows that experimental group post-test engagement scores $W = 0.931$, $p = 0.091$ (for cognitive construct $W = 0.887$, $p = 0.089$, for behavioral construct $W = 0.935$, $p = 0.111$, for social $W = 0.959$, $p = 0.404$, and for emotional $W = 0.939$, $p = 0.142$). These results demonstrate that post-test engagement scores and their components were normally distributed. The homogeneity regression slopes of the two groups' tests was confirmed, with $F = 0.672$ and $p > 0.05$, indicating the suitability of ANCOVA, as shown in Table 5.

TABLE 4 Shapiro–Wilk test of the normality.

Group	Dimension	Statistic	Df
Exp	Behavioral post	0.935	50
	Cognitive post	0.887	50
	Emotional post	0.939	50
	Social post	0.959	50
	post_total	0.931	50

> *RQ2.* What types of engagement occurred in AI-assisted microlearning in online learning?
>
> *RQ3.* How does AI-assisted microlearning influence engagement in online environment?

Comments in the discussion forums and their responses in interviews were analyzed by deductive and inductive content analysis, a method of systematically describing and analyzing the meaning of qualitative data. This approach begins with a theory or relevant research findings as guidance for initial codes (Hsieh and Shannon, 2005). The analysis of discussion forums, and semi-structured interview transcripts employed a dual approach combining inductive and deductive content analysis. Through inductive reasoning, key categories were derived from participant responses, allowing themes to emerge from the data. Simultaneously, a deductive framework was applied, structured around four predefined engagement dimensions: social, behavioral, emotional, and cognitive. The resulting engagement themes are presented in Table 4, demonstrating how microlearning influences different engagement facets. Using Bowden's framework, two researcher teams coded 1,250 comments via deductive content analysis (Hsieh and Shannon, 2005). Inter-coder reliability reached 87% consensus. AI tools (ChatGPT for quizzes, Canva AI for videos) delivered personalized microlearning modules. Using the "meaning" as the unit of analysis, 740 comments were calculated from a total of 1,250 comments. Thematic analysis process (Braun and Clarke, 2014) was conducted to identify patterns and address research questions. The process included: familiarization – repeatedly reading transcribed interviews to immerse in the data. Initial coding – manually labeling key features to generate concise codes. Theme development – grouping related codes into potential themes. Theme review – refining themes by reassessing their fit with the dataset. Defining and naming themes – finalizing themes with clear definitions. A coding book was created, as shown in Table 6 with theme percentages.

4.1 Trustworthiness and validation

To uphold the study's reliability and credibility, four key validation criteria were applied, including cross-referencing and expert validation. Forum responses were cross-checked with input from field experts during coding, resulting in an 85% inter-coder agreement rate, exceeding the standard 80% threshold. Credibility was ensured by verifying through code cross-checking, data verification, and discrepancy checks to ensure accuracy. Dependability was established through code–recode strategy. The dataset was independently coded twice with a 2-week gap between sessions to assess consistency. A stepwise replication approach was used, where both researchers analyzed data separately and compared outcomes. Transferability and conformability were checked by selecting purposive sampling that ensured participant selection aligned with study criteria. Researcher bias was minimized by strictly basing conclusions on participant narratives and maintaining detailed procedural records. A dual-check process was implemented throughout the study to confirm data accuracy.

TABLE 5 Test of homogeneity of regression slopes for total engagement.

Source	Type III sum of squares	Df	Mean square	*F*	Sig.
pre_total * group	0.221	3	0.074	0.672	0.581
Error	1.751	16	0.109		
Total	492.077	50			

R Squared = 0.948 (Adjusted *R* Squared = 0.840).
Dependent Variable: post_total.

TABLE 6 Coding book with theme percentages.

Theme	Key findings	Example	Percentage
Behavioral	Learners found adaptive quizzes effective for retention.	The video showed how to edit and add effects, we can create a video that is composed of so many images easily.	73%
Social	Peer discussions were underutilized; chatbots were popular.	"*Yes, the video was interesting, I can share it easily*"	65%
Emotional	Focuses on connection, value creation, and long-term relationship building	*"Video show is a good application, it is good for beginners since it only shows how to edit images and add some effects."* *It did not benefit met that much, since it did not explain how to write on images un the video!"*	42%
Cognitive	Understanding concepts, thinking, critical thinking	"*the video taught me how to edit images smoothly and with details*" "I can create interactive movies easily to, and there is so many features in this site to design a postures and brochures.	85%

4.2 Ethical considerations

The study received ethical approval from PTUK. Moreover, informed consent was obtained from all participants, confidentiality was maintained by anonymizing identities and storing data securely on a password-protected computer.

5 Results

> *RQ1*-Does AI-assisted microlearning have a significant impact on college student engagement?

ANCOVA was used to find the significant differences between the engagement scores of the two groups using the pre-test scores as the covariate and the post-test scores as the dependent variable, to enable comparison of the post-engagement scores by excluding the impact of the pre-test scores. Before conducting ANCOVA, an independent *t*-test was used to confirm whether the two groups had similar engagement level. Table 7 shows that no significant difference was found between the two groups' pre-test engagement scores.

Table 7 indicates no significant differences between the two groups with $t = -1.063$ ($p > 0.05$), indicating that the two groups were equivalent of engagement scores and the two classes had similar learning abilities until they had a basic understanding of the course. ANCOVA was conducted to determine whether there was a significant difference between the mean post-scale engagement scores of students who used AI-assisted microlearning and those who did not, as shown in Table 7.

Table 7 shows significant differences in student engagement after the experiment between the AI-assisted microlearning group and the control group. After controlling for pre- intervention engagement scale score, there was a significant effect of AI-assisted microlearning usage on engagement with $F(1, 47) = 23.88$, $p = 0.000$ for overall engagement, for cognitive component; $F(1, 47) = 41.17$, $p = 0.000$ for behavioral component; $F(1, 47) = 12.215$, $p = 0.000$ for emotional component; $F(1, 47) = 7.113$, $p = 0.000$ for social component, $F(1, 47) = 10.018$, $p = 0.000$ for overall engagement. A computation of R-squared (R^2) showed that $\eta^2 = 0.825$ for cognitive component, $\eta^2 = 0.849$ for behavioral, $\eta^2 = 0.413$ for emotional component, $\eta^2 = 0.634$ for social component, and $\eta^2 = 0.327$ for overall engagement. The previous results showed significant difference between engagement and its components of the group of students who used AI-assisted microlearning for educational technology course than the group of students who did not used it. These results imply that AI-assisted microlearning accounted for 86% of the total variance in engagement as a consequence of its usage. This accounting for the variance is more in the components of engagement, where the η2 values ranged between 0.413 which is considered medium and 0.839 which is considered high (Richardson et al., 2023).

1 The second question were answered in this study:

Four types of engagement were found when analyzing the comments of students in online discussions with a major theme of cognitive engagement that got the highest frequent percentage.

5.1 Behavioral engagement

All students responded to the instructor's questions and received comments from their peers on questions the instructor posted in the discussion forums, demonstrating learner–learner

TABLE 7 Analysis of covariance (ANCOVA) summary table for engagement and its component scores by group condition.

Dependent variable	Source	Type III sum of squares	Df	Mean square	*F*	Sig.	Partial eta squared
Behavioral post	Behavioral pre	1.587	1	1.587	4.306	0.043	0.084
	Group	12.215	1	12.215	33.135	0.000	0.413
Emotional post	Emotional-pre	1.007	1	1.007	2.524	0.119	0.051
	Group	7.113	1	7.113	63.379	0.000	0.634
Cognitive post	Cognitive	1.431	1	1.431	2.464	0.123	0.050
	Group	47.171	1	47.171	81.242	0.000	. 849
Social post	Social	0.088	1	0.088	0.289	0.594	0.006
	Group	10.018	1	10.018	21.872	0.000	0.327
	pre_total	0.361	1	0.361	3.220	0.079	0.067
Total post	Group	23.882	1	23.882	212.796	0.000	0.825

interaction. Students in this AI-assisted microlearning discussed and interacted more with peers. Comments illustrated this interaction, such as" *I do agree with you,"" Yes, the video about image editing is really helpful…, "I do think that you are right when you mentioned google sites. "*. Another participant added *"the short videos made it easy to keep up. I'd watch one on the bus and actually do the exercises because they did not feel like a chore."* Also, another *"The badges were silly but motivating—I wanted to 'collect' all the modules!." "I commented more in forums because the topics were specific and short."* Also, there was another interaction with the microlearning videos. Examples of this interaction is: "*This video explained lots of details in a short time and step by step guide to make a brochure from scratch," "the posted video is very comprehensive and easy to follow," "very helpful video, especially for multimedia course."* These findings indicate that AI-assisted microlearning was effective in stimulating different types of interaction, particularly peer interaction and content interaction.

5.1.1 Social engagement

Students expressed how AI-assisted microlearning facilitated their communication. A few students noted that AI-created content helped in communicating with virtual assistance, while minimizing their communication with peers and instructors.

5.1.2 Cognitive engagement

Cognitive engagement involved students actively focusing on and processing new information in AI- created micro content.

Most participants reported more personalized and accessible experiences, allowing them to engage with virtual content in a way that feels more natural and human-like. Taqwa mentioned, "I really enjoy appealing microlearning content like infographics and videos, they fit my learning style." Salma added "implementing leaderboards where I earn points for completing microlearning modules or quizzes helps me to understand concepts."

It seems that AI was able to adjust the difficulty level of subsequent challenges based on a learner's past performance, ensuring an engaging experience tailored to their skill level.

5.1.3 Emotional engagement

2 How does AI-assisted microlearning influence engagement in online environment?

In the present study, it was shown that microlearning improved four types of engagement, which emerged in student comments and semi-structured interviews. Four themes of engagement were identified. Below, each engagement dimension is elaborated.

5.2 Less frustration

AI-assisted microlearning significantly influenced emotional engagement by leveraging personalized, interactive, and adaptive learning techniques.

> AbdelAzziz stated, "*AI-based mini-videos made me feel relaxed and no stress compared to traditional lengthy videos. They are designed to fit my learning style, preferences, and knowledge levels, making me feel understood*." Jamal added, "*learning material in this course fosters a sense of belonging and value, increasing motivation and reducing frustration*." Nagham added, "*I did not panic before quizzes anymore. The 3-min recaps gave me just enough to feel prepared*." Momen confirmed, "*finally, no frustration starring at my screen for a long time, something that fits my attention span! I could focus without guilt*."

5.3 Sharing

Social engagement is defined as a process in which learners connect with different technologies through learner–interface interaction to support further learning. In this study, students demonstrated interaction by connecting with different technologies, information, and peers.

Some students reported that the AI-based mini videos were interesting with high quality and resolution. They made the concepts easier and explained them in detail, as Ali mentioned "*The sound is clear, the* *videos explain the information step by step, and explains in an easy and simple way, I can share information with my peers easily*." Also Shadi said "*the videos taught me how to make education more effective, collaborative and meaningful*." This implies that the videos were effective and support information generation and content sharing.

5.4 Grabbing attention

Cognitive engagement refers to a process of connecting specialized nodes or information sources together. In this type of engagement, learners interact with the content and peers, exchanging video content and sometime describing or explaining it.

Students in interviews mentioned that AI-based microcontent helped them stay attentive and focused on tasks, since tasks were bite-sized and did not require long attention. Most students confirmed that AI-assisted microlearning videos and tasks captured their attention easily. Many students became more attentive to AI-assisted microlearning activities because they included a variety of activities and mini-interactive instructional videos.

Nadia mentioned, "*AI-based micro-games drives me to stay focused and attentive*."

Moreover, integrating different micro-activities students to share knowledge and construct in peer interactions and pay attention to each other's' comments. Majd said "*I would have more chances to share my thoughts instantly since tasks are short and vides are short, this allows me to save more attention from my side and spend more time ask questions and receive answers from my online classmates, reading their answers helped to think critically*."

5.4.1 Personalized learning

Most students told us that the video explains how to create emails, design portfolios and web pages, and video editing techniques as one of the students commented "*I learned about google sites that I never knew about, the mini video taught me how to create the site smoothly and with rich details." Another student added. "In* an online learning environment for me as a learner, AI can analyze quiz results after each microlearning module. If I score low on questions related to handling difficult concepts, the system can recommend additional resources or modules focused on conflict resolution. "*The case-study snippets made me curious. I'd Google extra details after class*."

> *"Micro-quizzes highlighted gaps I did not know I had. It was humbling but useful." "I could replay the coding demos until it clicked. No need to ask the professor."*

5.4.2 Task completion

Behavioral engagement in microlearning environment includes task completion, discussion, and reflection. All these themes were recognized in transcripts.

Mini-instructional videos helped students to aggregate and share information with each other with elaboration about concepts and ideas in this course, such as commenting on the content of videos and trying to evaluate them and adding information to the content of these videos, as its size is small. Most students exhibited higher engagement metrics, completion rates, frequency of logins, and application of skills.

5.4.3 Competition

Using AI-based microlearning enabled students to fulfill a sense of competition. AI -based games provided players with rewards system. Students who answered correctly felt they were the best. Since everyone wanted to win, they competed to be winners.

> Eyad stated, "*I like AI-based ranking system, it motivates me to win the game, it's fun and challenging for me since I had the chance to compete with online classmates, being able to learn concepts while playing in a stress free environment*."

6 Discussion

The results suggest that the pre- and post-engagement mean scores of both groups improved, supporting the influence of AI-assisted microlearning for online teaching course. A major benefit is its capacity to cognitively engage students throughout their learning process.

Cognitive engagement emerged as the strongest theme in this study, primarily due to the nature of AI-assisted microlearning, which directly targets and enhances the mental processes involved in learning. This can be explained as AI-assisted microlearning enables interactive experiences by offering concise learning resources and delivering clear explanations on diverse course topics, which holds students' attention and improve their cognitive abilities. Additionally, AI-driven microcontent supports a tailored approach, aiding comprehension and retention—especially for learners with time constraints or those seeking deeper exploration of specific subjects. AI also provides real-time feedback on learner performance, enabling timely interventions when learners struggle with specific concepts. This capability is crucial for enhancing knowledge retention and ensuring that students can apply what they learn effectively. AI-assisted microlearning optimizes cognitive processes such as attention, memory, understanding, and application. The AI tools used in this study (e.g., ChatGPT for quizzes, Canva AI for videos) were tailored to deliver bite-sized content that reduces cognitive load by providing personalized pathways adapted to individual learners' knowledge levels and pacing. These outcomes align with Boumalek et al. (2024), who found that AI can enhance retention and cognition by empowering students to direct their own learning through adaptable resources, fostering lifelong learning. This study provides empirical evidence that incorporating generative AI in microlearning design can lead to greater engagement among students.

Based on student interviews reported in the section related to RQ2, the discrepancies between the two groups reflect different levels of comprehension, participation, online interaction, and feelings. According to Fidan (2023) and Kohnke et al. (2025) microlearning enhanced willingness to participate in class activities. Moreover, AlMuqhim and Berri (2025) proposed AI-driven personalized microlearning for online courses for higher education and reported that computer science students use of highly tailored learning experiences enhanced their engagement. Responses from discussion forums and semi-structured interviews supported quantitative results, confirming that AI-assisted microlearning enhanced cognitive engagement as a main theme. It appears that AI-assisted microlearning facilitates a low cognitive load approach by enhancing participation and autonomy in using this technology.

Regarding the third question—how AI-assisted microlearning impacts engagement in online learning—four key themes arose, with *personalized learning* being the most prominent. The use of AI in microlearning allows learners to engage in customized online activities, such as interacting with AI-generated content and completing targeted exercises. AI streamlined access to tailored microlearning materials, enabling students to practice specific skills or concepts effectively within the online learning environment. This aligns with Alias and Razak (2025), who found that microlearning strategies that ranges from bite-sized content to video-based learning and social learning were effective in different contexts. AI algorithms analyze individual learner data to tailor content delivery based on unique preferences and needs. For instance, some platforms utilize AI to create customized learning pathways that adapt to each student skill level and learning pace. This personalization ensures that learners receive relevant information when they need it most.

For social engagement, students negotiated with each other about the micro-content, presented their thinking, and supported each other's opinions in comments and responses. For example, ChatGPT-powered quizzes offered after a 2-min video enabled learners to answer questions shortly. Moreover, AI-assisted microlearning influenced emotional engagement. This is could be explained due to short sessions of micro videos and microcontent and short quizzes, which prevented cognitive overload. AI personalization of micro content adapted to individual emotional needs and making learning more fun with more comfort. Also, AI-generated immediate feedback and progress tracking created positive reinforcement cycles. Emotional rewards (e.g., badges, progress bars) increased motivation, which in turn sustained behavioral participation. This feedback loop mirrors operant conditioning principles, where timely reinforcement strengthens desired learning behaviors.

7 Conclusion and future work

Based on the results, investigation of the intersection between generative AI and microlearning highlights its potentials for enhancing engagement in educational practices. Cognitive engagement emerged as the main theme among other dimensions. AI-assisted microlearning motivates students to remember concepts easily. Students interact with AI-based microcontent more than traditional online content. Future research is needed for a comprehensive approach that considers several technological factors. Also, more studies should be conducted for both prospective and continuing students with unique requirements with a focus on leveraging AI to meet their needs effectively. Moreover, there is a need to explore how higher educational institutions can provide personalized learning experiences tailored to meet individual student circumstances and needs. AI-assisted microlearning is transforming education by enhancing cognitive engagement by personalized and adaptive learning. AI tailors' content to individual learning styles, speeds, and knowledge gaps (Alias and Razak, 2025). AI-assisted microlearning also boosts focus through bite-sized, interactive content (Kossen and Ooi, 2021) by generating quizzes that reinforce concepts just before forgetting occurs.

7.1 Limitations

This study is limited by its single-institution sample and focus on technology students, which may affect generalizability. The quasi-experimental design, while practical, lacks random assignment. Future replications should include randomized control trials across disciplines. Also, the study employed a relatively small sample size (N = 50) drawn from a single academic program (Technology Education) at one university. This limited sample reduces statistical power for detecting smaller effects and constrains the generalizability of findings to broader student populations. The homogeneity of participants—all pre-service technology teachers with similar digital competencies—further limits applicability to students from other disciplines, academic levels, or with varying technological proficiencies. Moreover, despite efforts to ensure group equivalence through stratified assignment, the study utilized a quasi-experimental design rather than true randomization. Participants were not randomly assigned from a larger population but were instead enrolled in a specific course section, introducing potential selection bias. Although statistical tests indicated no significant pre-intervention differences between groups, unmeasured confounding variables (e.g., intrinsic motivation, prior online learning experience) may have influenced outcomes.

7.2 Future research

Future studies should recruit participants from both technical and non-technical programs across 3–5 universities. While this study focused on multimedia students, replication with larger, randomized samples is recommended. Moreover, future research could extend the limits beyond Engagement and examine effects on deeper learning outcomes including critical thinking, problem-solving transfer, and metacognitive skill development. Also, equity considerations could be investigated by conducting studies that explore whether AI-assisted microlearning reduces or exacerbates achievement gaps for underrepresented or academically at-risk student populations.

Data availability statement

The data that support the findings of this study are not publicly available due to privacy restrictions but are available from the corresponding author Reham Salhab with a reasonable request.

Ethics statement

The studies involving humans were approved by Prof. Jehad Asad/Palestine Technical University IRB. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

RS: Conceptualization, Investigation, Writing – review & editing, Writing – original draft. MA: Visualization, Resources, Funding acquisition, Conceptualization, Writing – review & editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was not used in the creation of this manuscript.

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