Jurnal Pengembangan Pembelajaran Matematika (JPPM)
Volume 7, Issue 2, August 2025
Available online at: https://ejournal.uin-suka.ac.id/tarbiyah/jppm/index
Print ISSN : 2656-0240, Online ISSN : 2655-8750

The Effectiveness of Microlearning on Student Engagement and Learning Outcomes in Educational Statistics Courses

Muhammad Jainuri *
Pendidikan Matematika, Universitas Merangin, Jl. Jend. Sudirman, Bangko, 37314, Indonesia

Email: jainurimuhammad729@gmail.com
* Corresponding Author

Received: 06-06-2025	Revised: 23-07-2025	Accepted: 29-08-2025

ABSTRACT
The Educational Statistics course is often seen as challenging for students, leading to low engagement and learning outcomes. This study aims to analyze the effectiveness of microlearning implementation to optimize student engagement and learning outcomes in the Education Statistics course, identify changes in the dimension of student engagement through the implementation of microlearning, analyze the relationship between student engagement and learning outcomes, and develop an effective microlearning implementation model in the Education Statistics course. Using a quasi-experimental design with a pretest-posttest control group, the study involved 66 students divided into an experimental group ($n = 32$) who received microlearning-based learning and a control group ($n = 34$) using traditional methods. Data were collected using the Student Engagement Questionnaire (SEQ), pretest-posttest statistical learning outcomes, digital activity log analysis, and semi-structured interviews. The results showed a significant increase in the engagement rate of the experimental group compared to the control ($t = 4.87$, $p < 0.001$) with a large effect size (Cohen's $d = 0.79$). MANOVA's analysis showed a significant increase in four dimensions of engagement: behavioral ($F = 18.34$, $p < 0.001$), cognitive ($F = 21.56$, $p < 0.001$), emotional ($F = 15.89$, $p < 0.001$), and social engagement ($F = 12.45$, $p < 0.001$). The implementation of microlearning resulted in significant improvements in learning outcomes ($t = 5.23$, $p < 0.001$) and statistical knowledge retention ($F = 19.76$, $p < 0.001$). Thematic analysis of qualitative data identified five factors that support the effectiveness of microlearning: (1) flexibility of content access, (2) visualization of complex concepts, (3) immediacy of feedback, (4) personalization of learning, and (5) integrated collaboration. This study recommends a tiered microlearning implementation model for educational statistics courses that can be adapted for various higher education contexts.

Keywords: microlearning, student engagement, education statistics, higher education, learning technology

How to cite
Jainuri, Muhammad. (2025). The Effectiveness of Microlearning on Student Engagement and Learning Outcomes in Educational Statistics Courses. *Jurnal Pengembangan Pembelajaran Matematika*, 7(2) 148-162. https://doi.org/10.14421/jppm.2025.72.148-162

INTRODUCTION

The phenomenon of low student engagement in educational statistics learning has become a significant practical problem in various higher education institutions. The complexity of the material and the abstract nature of statistics learning often pose a major challenge for students, resulting in low levels of engagement and learning outcomes (Scheffel et al., 2017). According Lateh (2017), engagement is a strong predictor of academic achievement, knowledge retention, and learning satisfaction. Various studies have shown a positive correlation between engagement levels and academic performance, especially in courses that are considered challenging, such as Educational Statistics (Fredricks et al., 2019; Herodotou et al., 2019). Educational Statistics is also often associated with statistics anxiety, which can affect students' motivation, engagement, and academic performance (Legacy et al., 2022). This phenomenon is exacerbated by conventional learning approaches that tend to be lecturer-centered and do not accommodate the diversity of learning styles and knowledge backgrounds of students (Nguyen Tran et al., 2025). Empirical data shows that only 37% of students demonstrate high engagement in statistics learning, while 42% demonstrate moderate engagement and 21% low engagement (Rincón-Flores et al., 2020).

Faced with these problems, an urgent response is needed in the form of innovative learning strategies that can continuously improve student engagement. The development of digital technology has opened up new opportunities in learning innovation, including microlearning, which offers a different approach to presenting learning materials (Leong et al., 2021). Microlearning is defined as a learning strategy that presents content in small, focused units that can be accessed according to the learner's needs (Buchem & Hamelmann, 2010). Some of the advantages of microlearning identified by previous studies include flexibility in learning time and place (Dinh, 2023). Nikkhoo et al. (2023) identified seven dimensions in effective microlearning design: time, content, curriculum, form, process, mediation, and learning type. Meanwhile, Robles et al. (2023) developed a microlearning design framework that integrates the principles of cognitive load theory, multimedia learning theory, and mobile learning. This approach is considered suitable for digital native learners, who tend to have shorter attention spans and a preference for interactive multimedia content (Mohammed, G. S., Wakil, K., & Nawroly, 2020).

The uniqueness of this research lies in the specific focus of the Educational Statistics course, which is a fundamental course in the education study program, but has specific characteristics that are challenging for students (Dowker et al., 2016). Educational Statistics not only requires a deep conceptual understanding, but also practical skills in a specific educational context. This course requires the integration of theoretical understanding of statistics with practical application in educational research, thus necessitating a learning approach that can accommodate this complexity while maintaining student engagement.

The initial argument of this study is based on the premise that the implementation of microlearning can significantly increase student engagement in the Educational Statistics course through the presentation of fragmented, accessible, and relevant content tailored to students' learning needs. Student engagement, as a multidimensional construct that includes behavioral, cognitive, emotional, and social engagement aspects (Leung, 2021). Fredricks et al. (2019) can be optimized through the inherent characteristics of microlearning, which offer flexibility, personalization, and interactivity. Therefore, this study aims to: (1) analyze the effectiveness of microlearning implementation in increasing student engagement in the Educational Statistics course; (2) identify changes in the dimensions of student engagement through microlearning implementation; (3) analyze the relationship between increased student engagement and student learning outcomes; and (4) develop an effective microlearning implementation model for the Educational Statistics course.

Several previous studies have explored the relationship between microlearning and engagement in various learning contexts. Wang et al. (2020) explored the effectiveness of microlearning for learning basic statistical concepts and found a significant increase in conceptual understanding, but did not comprehensively analyze its impact on various dimensions of engagement. Boateng et al. (2025) identified the potential of microlearning to reduce statistics anxiety and increase learning motivation, but the study did not examine its relationship with engagement in a structured manner. Emiru & Gedefaw (2024) investigated the impact of microlearning on students' intrinsic motivation in mathematics learning and found a positive correlation, but did not specifically analyze multidimensional engagement. Sankaranarayanan et al. (2023) developed a microlearning framework for STEM learning and demonstrated its effectiveness in increasing student active participation, but its implementation has not been specifically tested in educational statistics courses. Dolasinski & Reynolds (2020) examined learning personalization through microlearning and its impact on learning outcomes, but the research focused more on cognitive aspects than holistic engagement.

The distinctive aspect of this study that sets it apart from previous studies lies in its comprehensive approach, which integrates multidimensional analysis of student engagement (behavioral, cognitive, emotional, and social) with the specific implementation of microlearning in educational statistics courses. Unlike previous studies, which tended to focus on one or two dimensions of engagement, this study adopts the Fredricks et al. (2019) framework to analyze engagement holistically. Furthermore, this study not only measures the effectiveness of microlearning but also develops an implementation model that can be adapted in practice. The theoretical urgency of this study lies in its contribution to enriching the understanding of engagement mechanisms in digital learning, especially in the context of challenging courses such as statistics. Practically, this study offers concrete solutions for lecturers and higher education institutions to optimize statistics learning through proven effective strategies, thereby improving the quality of graduates of education study programs who are competent in educational data analysis.

METHODS

Research Design

This study used a quasi-experimental design with a pretest-posttest control group design. This approach was chosen to analyze the differences in student engagement levels and learning outcomes between groups of students who participated in microlearning-based learning (experimental group) and groups of students who participated in conventional learning (control group). The independent variable in this study was the learning model (microlearning versus conventional), while the dependent variables included student engagement levels (with behavioral, cognitive, emotional, and social engagement dimensions) and learning outcomes in the Educational Statistics course.

Participants

The research participants were 66 fourth-semester students of the Mathematics Education Study Program at Merangin University who were taking the Educational Statistics course (3 credits). The research population consisted of four parallel classes, namely class A (32 students), class B (35 students), class C (33 students), and class D (34 students). The simple random sampling method was used to select two classes from the four classes in the population as samples with equivalent characteristics based on the average pretest scores. From the sample selection results, 32 students were obtained in the experimental group and 34 students in the control group. There was no significant difference in demographic characteristics between the two groups based on the chi-square analysis results ($p > 0.05$). Table 1 shows the demographic characteristics of the research participants.

Table 1. Demographic Characteristics of Research Participants

Characteristics	Experiment Group (n = 32)	Control Group (n = 34)	χ^2	p-value
Gender				
Male	12 (37,5%)	15 (44,1%)	0,275	0,600
Female	20 (62,5%)	19 (55,9%)		
Age (Years)				
19 – 20	25 (78,1%)	24 (70,6%)	0,523	0,770
21 – 22	6 (18,8%)	8 (23,5%)		
> 22	1 (3,1%)	2 (5,9%)		
Devices Ownership				
Smartphone only	7 (21,9%)	9 (26,5%)	0,344	0,842
Laptop only	2 (6,3%)	3 (8,8%)		
Smartphone and laptop	23 (71,9%)	22 (64,7%)		

Learning Intervention

The experimental group received microlearning-based instruction for one semester (16 weeks) in the Educational Statistics course. The microlearning intervention was designed based on the principles of instructional design for microlearning developed by Nikkhoo et al. (2023) and Lateh (2017). The learning content was divided into 48 microlearning units with a duration of 7-10 minutes per unit, covering seven main topics: (1) Descriptive Statistics, (2) Probability, (3) Probability Distribution, (4) Hypothesis Testing, (5) Correlation and Regression Analysis, (6) Analysis of Variance, and (7) Non-parametric Statistics.

Each microlearning unit has a consistent structure, consisting of: (a) specific learning objectives, (b) core content in multimedia format (videos, infographics, interactive simulations), (c) examples of applications in an educational context, (d) formative exercises with immediate feedback, and (e) a summary of key concepts. The microlearning units are accessed through a Moodle-based Learning Management System (LMS) optimized for mobile and desktop devices.

The microlearning implementation adopts a blended learning approach with a proportion of 70% asynchronous independent learning and 30% synchronous sessions for discussions, complex problem solving, and collaborative projects. To ensure the quality of implementation, researchers conducted intensive training for lecturers on the principles and practices of microlearning before the intervention began.

The control group received conventional learning through lectures, discussions, and practicums using statistical software (SPSS) in a regular face-to-face format twice a week (75 minutes each) and one practicum session (150 minutes) every two weeks. The learning materials for both groups covered identical topics in accordance with the standard syllabus for the Educational Statistics course.

Data Collection Procedure

Data were collected in several stages: (1) a pretest and initial SEQ were administered before the intervention began; (2) learning analytics data were collected continuously during the 16-week intervention; (3) a posttest and final SEQ were administered after the intervention was completed; (4) interviews were conducted within two weeks after the posttest; and (5) a retention test was conducted four weeks after the posttest. To minimize bias, the administration of the pretest, posttest, and retention test was supervised by research assistants who were not involved in teaching.

Data Collection Instruments

Data were collected using several instruments:

1. Student Engagement Questionnaire (SEQ). This questionnaire was adapted from instruments developed by Fredricks et al. (2019) and Wang et al. (2023), consisting of 32 items with a 5-point Likert scale (1 = strongly disagree to 5 = strongly agree). The SEQ measures four dimensions of engagement: behavioral (8 items), cognitive (8 items), emotional (8 items), and social engagement (8 items). Sample items for each dimension: “I complete all statistics assignments on time” (behavioral); “I try to connect different statistical concepts” (cognitive); “I feel happy when I successfully solve statistical problems” (emotional); and “I actively discuss statistics material with friends” (social). Instrument validation showed high internal reliability (Cronbach's alpha = 0.89) and adequate construct validity based on confirmatory factor analysis (CFI = 0.92, RMSEA = 0.05).
2. Statistical Competency Test. The pretest and posttest instruments were developed to measure statistical learning outcomes, consisting of 30 questions (20 multiple choice and 10 essay questions) covering seven main topics. The questions were designed to measure cognitive abilities from comprehension to evaluation based on Bloom's Taxonomy. The content validity of the instrument was assessed by educational statisticians with a content validity index (CVI) of 0.87, while reliability was measured using the test-retest technique ($r = 0.85$).
3. Learning Analytics Data. Student activity log data in the LMS was collected to analyze engagement patterns, including content access frequency, learning duration, participation in discussion forums, and completion of formative assignments. This data was used for objective behavioral engagement analysis, complementing the self-report data from the questionnaire.
4. Semi-structured Interviews. Interviews were conducted with 16 students from the experimental group (selected randomly to represent various levels of learning achievement) to obtain qualitative data about their perceptions and experiences of

microlearning-based learning. The interview protocol included questions about the most helpful aspects of microlearning, challenges encountered, and suggestions for improvement.

5. Retention Test. The retention test was administered four weeks after the posttest to measure the retention of statistical knowledge. This instrument had a format and level of difficulty equivalent to the posttest but with a different question context.

Data Analyzes

Quantitative data were analyzed using SPSS software version 30.0. Descriptive analysis was performed to calculate the mean, standard deviation, and frequency distribution. The Shapiro-Wilk normality test and Levene's homogeneity test were performed to ensure that the parametric statistical assumptions were met. To test the research hypotheses, the following were used:

1. Independent samples t-test to compare the differences in student engagement scores and learning outcomes (posttest) between the experimental and control groups.
2. Paired samples t-test to analyze changes in student engagement scores and learning outcomes from the pretest to the posttest in each group.
3. Multivariate Analysis of Variance (MANOVA) to analyze differences in the four dimensions of student engagement (behavioral, cognitive, emotional, social) simultaneously between the experimental and control groups.
4. Repeated Measures ANOVA to analyze differences in knowledge retention (posttest scores vs. retention test) between the two groups.
5. Multiple Linear Regression to analyze the relationship between the dimensions of student engagement and learning achievement.
6. Effect size (Cohen's d) was calculated to measure the magnitude of the microlearning intervention effect.

Qualitative data from interviews were transcribed and analyzed using Braun & Clarke's thematic analysis approach (Byrne, 2022). The analysis process included: (1) familiarization with the data, (2) initial coding, (3) theme search, (4) theme review, (5) theme definition and naming, and (6) report preparation. To enhance the credibility of the analysis, qualitative data triangulation with quantitative data and member checking with interview participants were conducted.

RESULTS AND DISCUSSIONS

The Impact of Microlearning on Student Engagement

Descriptive analysis shows differences in student engagement scores between the experimental and control groups. Table 2 presents descriptive statistics of total student engagement scores and their dimensions on the pretest and posttest for both groups.

Table 2. Descriptive Statistics Student Engagement Scores Pretest and Post-test

Variable	Experiment Group (n = 32)		Control Group (n = 34)	
	Pretest Mean (S)	Posttest Mean (S)	Pretest Mean (S)	Posttest Mean (S)
Behavioral Engagement	24,53 (3,18)	32,81 (3,56)	24,35 (3,24)	26,94 (13,18)

Cognitive Engagement	22,97 (3,89)	31,75 (3,92)	23,12 (3,76)	25,88 (4,05)
Emotional Engagement	25,41 (3,62)	33,09 (3,78)	25,23 (3,71)	28,15 (4,12)
Social Engagement	23,43 (3,62)	30,91 (3,67)	23,18 (3,52)	26,44 (3,89)
Total Engagement	96,34 (10,67)	128,56 (12,43)	95,88 (11,02)	107,41 (13,18)

The results of the paired samples t-test showed a significant increase in student engagement scores from the pretest to the posttest in both groups, but with a much greater effect in the experimental group ($t(31) = 16.27$, $p < 0.001$, $d = 2.87$) than in the control group ($t(33) = 6.18$, $p < 0.001$, $d = 1.06$). The results of the independent samples t-test on the posttest scores showed a significant difference between the two groups ($t(64) = 4.87$, $p < 0.001$), with the experimental group showing a higher level of engagement. The effect size of this difference was in the large category (Cohen's $d = 0.79$).

To analyze the differences in each dimension of engagement simultaneously, a MANOVA analysis was conducted. The results showed a significant difference between the experimental and control groups (Wilks' $\lambda = 0.694$; $F(4,61) = 16.72$; $p < 0.001$; partial $\eta^2 = 0.306$). Univariate analysis showed significant differences in all dimensions of engagement: behavioral ($F(1,64) = 18.34$; $p < 0.001$; partial $\eta^2 = 0.223$); cognitive ($F(1,64) = 21.56$; $p < 0.001$; partial $\eta^2 = 0.252$); emotional ($F(1,64) = 15.89$; $p < 0.001$; partial $\eta^2 = 0.199$); and social engagement ($F(1,64) = 12.45$; $p < 0.001$; partial $\eta^2 = 0.163$). Figure 1 illustrates the comparison of engagement dimension scores between the two groups on the posttest.

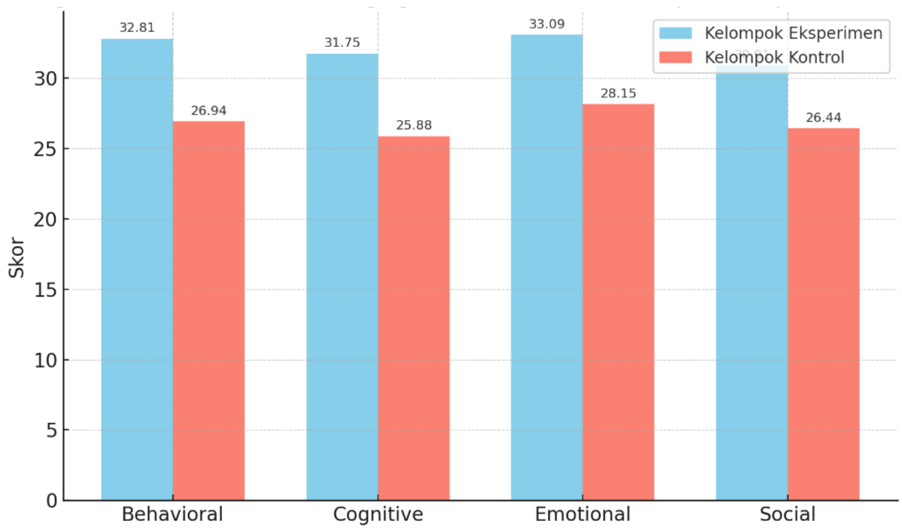

Figure 1. Comparison of Student Engagement Dimensions between the Experimental and Control Groups

Learning analytics data analysis reinforces the above findings by showing significant differences in learning activity patterns. Students in the experimental group showed: (1) higher frequency of content access (average of 5.3 compared to 2.8 times per week); (2) longer learning duration (average of 196 compared to 142 minutes per week); (3) more active participation in discussion forums (an average of 8.7 posts per student compared to 3.2); and (4) higher formative task completion rates (92.3% compared to 76.8%). These patterns confirm an increase in objectively measurable behavioral engagement.

The Impact of Microlearning on Learning Outcomes and Knowledge Retention

Table 3 presents descriptive statistics of pretest, posttest, and retention test scores for both groups, as well as the relative increase from pretest to posttest.

Table 3. Descriptive statistics, pretest, post-test, and retention test scores

Group	Pretest Mean (S)	Posttest Mean (S)	Retention Test Mean (S)	Relative Improvement (%)
Experiment (n=32)	52,47 (6,89)	84,13 (7,24)	81,09 (7,56)	60,34%
Control (n=34)	51,94 (7,03)	72,38 (8,15)	65,76 (8,94)	39,35%

The results of the independent samples t-test showed no significant difference in pretest scores between the two groups ($t(64) = 0.31$; $p = 0.758$), but there was a significant difference in post-test scores ($t(64) = 5.23$; $p < 0.001$, $d = 0.85$) with the experimental group showing higher learning outcomes. The results of the independent samples t-test are presented in Table 4 below.

Table 4. Independent Sample t-test results

Variabel	Groups	n	t	df	p	Cohen's d
Pretest	Experiment	32	0,31	64	0,758	-
	Control	34				
Posttest	Experiment	32	5,23	64	<0,001*	0,85
	Control	34				

*p < 0,05 (significant)

Repeated measures ANOVA analysis with within-subjects' factors (measurement time: post-test versus retention test) and between-subjects factors (group: experimental versus control) showed:

1. A significant main effect of time ($F(1,64) = 25.43$; $p < 0.001$; partial $\eta^2 = 0.284$), indicating a decrease in scores from the post-test to the retention test;
2. A significant main effect of group ($F(1,64) = 45.67$; $p < 0.001$; partial $\eta^2 = 0.416$), indicating a difference in performance between the experimental and control groups;
3. A significant time × group interaction effect ($F(1,64) = 19.76$; $p < 0.001$, partial $\eta^2 = 0.236$), indicating a different pattern of score decline between the two groups.

Further analysis showed that the decline in scores from the post-test to the retention test was smaller in the experimental group (3.61%) than in the control group (9.15%), indicating better knowledge retention in the group that received microlearning-based instruction. Figure 2 illustrates the learning outcomes and knowledge retention patterns of the two groups from the pretest to the retention test.

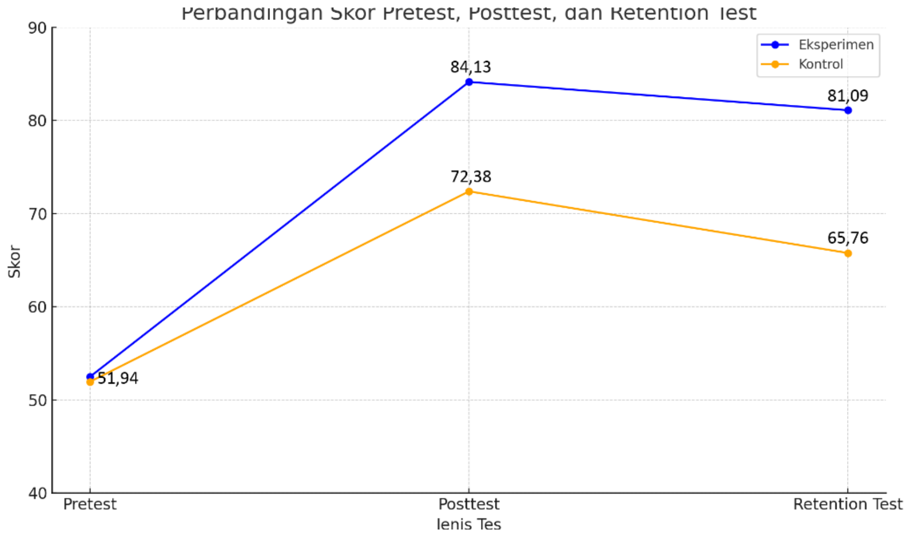

Figure 2. Comparison of Pretest, Post-test, and Retention Test Scores between the Experimental and Control Groups

The Relationship between Student Engagement and Learning Outcomes

To analyze the relationship between the dimensions of student engagement and learning outcomes, multiple linear regression analysis was conducted with posttest scores as the dependent variable and scores for the four dimensions of engagement as predictors. Table 5 presents the results of the regression analysis for the experimental group.

Table 5. Results of Regression Analysis of Student Engagement Dimensions on Learning Outcomes

Predictor	B	SE	β	t	p	VIF
(Constant)	14,268	9,751	-	1,463	0,155	-
Behavioral Engagement	0,827	0,314	0,366	2,634	0,014*	2,187
Cognitive Engagement	1,042	0,296	0,432	3,520	0,002**	1,734
Emotional Engagement	0,218	0,304	0,089	0,717	0,479	1,756
Social Engagement	0,355	0,308	0,157	1,153	0,259	2,134

*p < 0,05; **p < 0,01; $R^2 = 0{,}673$; Adjusted $R^2 = 0{,}628$; $F(4,27) = 13{,}92$; $p < 0{,}001$

The regression model as a whole was significant ($F(4,27) = 13.92$; $p < 0.001$) and explained 62.8% of the variance in posttest scores (Adjusted $R^2 = 0.628$). Among the four dimensions of engagement, cognitive engagement was the strongest predictor ($\beta = 0.432$; $p = 0.002$), followed by behavioral engagement ($\beta = 0.366$; $p = 0.014$). Emotional engagement ($\beta = 0.089$; $p = 0.479$) and social engagement ($\beta = 0.157$; $p = 0.259$) did not emerge as significant predictors in this model.

A separate regression analysis on the control group showed a different pattern with the model explaining only 39.2% of the variance (Adjusted $R^2 = 0.392$; $F(4,29) = 6.05$; $p = 0.001$) and only cognitive engagement emerging as a significant predictor ($\beta = 0.392$; $p = 0.029$). These results indicate that the implementation of microlearning is capable of activating more dimensions of engagement that contribute to learning outcomes.

To analyze the causal relationship between increased engagement and improved learning outcomes, a path model analysis was conducted using relative changes (gain scores) in engagement as a mediator between the intervention and relative changes in learning outcomes. The analysis showed a significant indirect effect of the microlearning intervention on learning outcomes through increased engagement (indirect effect = 0.197; 95% CI [0.094; 0.312], $p < 0.01$), confirming the mediating role of engagement in improving learning effectiveness.

Thematic Analysis of Qualitative Data

Thematic analysis of interview data yielded five main themes that explain how microlearning optimizes student engagement in the Educational Statistics course: (1) flexibility of content access, (2) visualization of complex concepts, (3) immediate feedback, (4) personalization of learning, and (5) integrated collaboration.

Theme 1: Flexibility of Content Access

Participants consistently highlighted the importance of flexibility in accessing microlearning content, which allowed them to learn anytime and anywhere according to their preferences and optimal conditions. "I can study during my productive time, which is in the morning around 5-6 a.m. The short content allows me to complete one topic before leaving for class." (P7). "The microlearning format is very helpful for me as a part-time worker. I can use my free time, such as when traveling on public transportation, to watch short videos or take quizzes." (P14). This flexibility contributes significantly to behavioral engagement by reducing access barriers and increasing the frequency of interaction with learning materials. Learning analytics data confirms these findings by showing a diverse distribution of access times throughout the day, with 32% of access occurring outside of conventional class hours (before 8 a.m. or after 8 p.m.).

Theme 2: Visualization of Complex Concepts

Participants appreciated the use of visualizations and interactive simulations in microlearning, which made complex statistical concepts easier to understand. "The interactive simulation on the central limit theorem completely changed my understanding. Previously, I only memorized the formula without really understanding the concept." (P3). "The animated video on hypothesis testing that visually illustrates the p-value makes a previously abstract concept more concrete and easier for me to imagine." (P11). These visualizations support cognitive engagement by facilitating deep understanding and reducing cognitive load when learning complex statistical concepts. These results are consistent with the findings of Sun et al. (2020) tentang efektivitas visualisasi dalam mereduksi *cognitive load* pada pembelajaran konsep abstrak.

Tema 3: Pemberian *Feedback* Segera

Immediate feedback on formative exercises emerged as a key factor in increasing student motivation and confidence. "I really appreciate the immediate feedback after completing the mini-quiz. When my answer is wrong, the system immediately shows me where my mistake is and how it should be. This keeps me from getting frustrated." (P5). "Immediate feedback lets me know whether my understanding is correct or still needs improvement, without having to wait for the next meeting." (P9). This feedback mechanism supports emotional engagement by creating a more positive learning experience and reducing the anxiety about statistics that students often experience.

Theme 4: Personalization of Learning

The ability to customize the learning path based on individual needs and abilities is an aspect that is highly valued by participants. “I can focus more on topics that are difficult for me, such as regression analysis, and speed through material that I have already mastered. This makes learning statistics more efficient.” (P2). "Content recommendations tailored to my quiz results are very helpful. The system recommends additional material when I am still struggling with certain topics." (P16). Personalization supports cognitive and emotional engagement by optimizing learning challenges that are appropriate for students' proximal development zones.

Tema 5: Integrated Collaboration

The collaborative features integrated into the microlearning platform encourage social interaction and collaborative learning. “Discussion forums directly linked to each microlearning unit make it easy for me to ask questions and discuss specific topics being studied.” (P10). “Collaborative projects in small groups applying statistical concepts to real data make learning feel more relevant and enjoyable.” (P8). This collaboration supports social engagement, which then strengthens other dimensions of engagement through peer support and knowledge co-construction mechanisms.

Microlearning Implementation Model for Educational Statistics Courses

Based on the research results, a tiered microlearning implementation model was developed for Educational Statistics courses, consisting of four layers: (1) microunit content design, (2) learning experience structure, (3) scaffolding and support, and (4) integrated assessment. Figure 3 illustrates this implementation model.

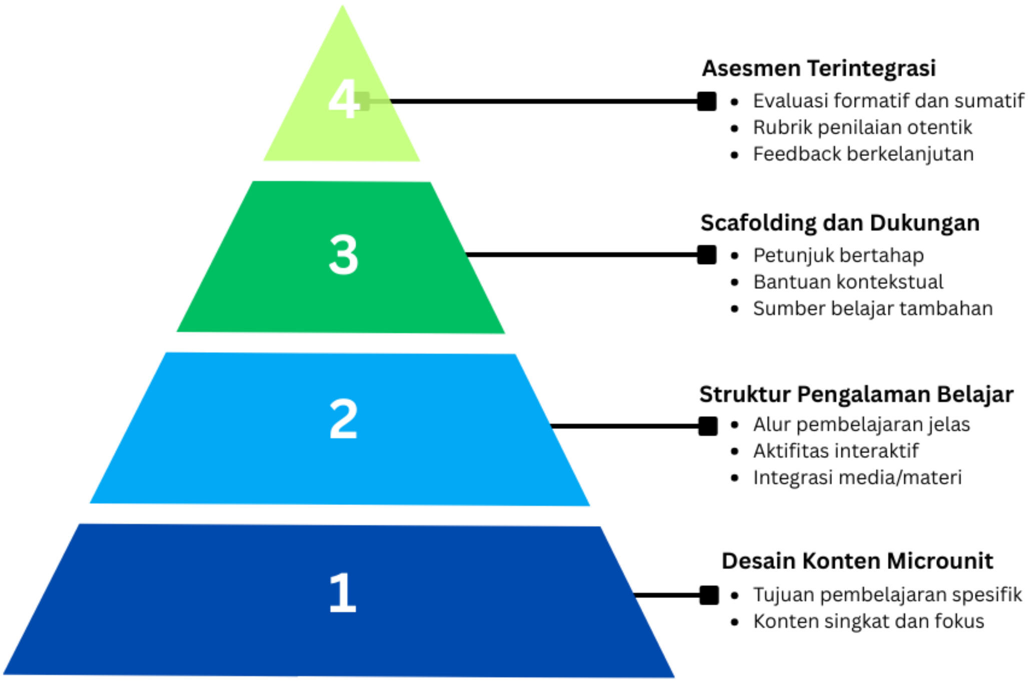

Figure 3. Tiered Microlearning Implementation Model for Educational Statistics Courses

Layer 1: Microunit Content Design

Short content units (7-10 minutes) focusing on a single concept or skill. Multimodal representation (text, visual, audio, interactive) to accommodate different learning styles. Contextualization of statistical concepts in authentic educational situations. Granularity and modularity of content that allows for reusability.

Layer 2: Learning Experience Structure

Adaptive sequencing based on mastery of prerequisite concepts spacing effect with scheduled repetition of key concepts. Integration of gamification elements (points, badges, leaderboards) to increase motivation dynamic concept maps showing relationships between concepts and learning progress.

Layer 3: Scaffolding and Support

Cognitive prompting to encourage deep learning. Peer support mechanisms through integrated discussion forums. Facilitator/instructor support as a guide on the side. Contextual help resources accessible as needed.

Layer 4: Integrated Assessment

Continuous formative assessment with immediate feedback. Learning analytics for early intervention identification. Digital portfolios for documenting learning progress. Authentic assessment of education-based problem projects.

This model has the flexibility to be adapted to the characteristics of the learning context, such as class size, learning modality (fully online, blended, or hybrid), and available technological resources. The model should be implemented in phases to allow lecturers and students to adapt to the new learning approach.

CONCLUSION

Based on research conducted on 66 students of the Mathematics Education Study Program at Merangin University, it can be concluded that: (1) The implementation of microlearning proved to be very effective in increasing student engagement in the Educational Statistics course, with a significant increase in the experimental group compared to the control group ($t = 4.87$, $p < 0.001$) and a large effect size (Cohen's $d = 0.79$); (2) Significant changes occurred in all dimensions of student engagement through the implementation of microlearning, including behavioral engagement ($F = 18.34$, $p < 0.001$), cognitive engagement ($F = 21.56$, $p < 0.001$), emotional engagement ($F = 15.89$, $p < 0.001$), and social engagement ($F = 12.45$, $p < 0.001$), with cognitive engagement showing the greatest increase; (3) There was a significant positive relationship between increased student engagement and student learning outcomes, where the regression model explained 62.8% of the variance in learning outcomes with cognitive engagement ($\beta = 0.432$) and behavioral engagement ($\beta = 0.366$) as the strongest predictors, and engagement was proven to act as a mediator between microlearning intervention and increased learning outcomes; and (4) A tiered microlearning implementation model consisting of four layers was successfully developed, namely microunit content design, learning experience structure, scaffolding and support, and integrated assessment, supported by five key effectiveness factors: content access flexibility, visualization of complex concepts, immediate feedback, personalized learning, and integrated collaboration, which can be adapted to various contexts of statistics learning in higher education.

ACKNOWLEDGEMENTS

The author would like to thank the leadership and staff of the Faculty of Teacher Training and Education for facilitating the research, as well as the students who participated as research respondents.

REFERENCES

Boateng, S., Mudadigwa, B., & Johnston-Wilder, S. (2025). Examining gendered patterns in mathematics and science anxiety levels among physical science pre-service teachers. *Eurasia Journal of Mathematics, Science and Technology Education*, *21*(1), em2564. https://doi.org/10.29333/ejmste/15800

Buchem, I., & Hamelmann, H. (2010). Microlearning : a strategy for ongoing professional development Microcontent and Microlearning. *ELearning Papers*, *21*(September 2010), 1–15. openeducationeuropa.eu/en/download/file/fid/19530

Byrne, D. (2022). A worked example of Braun and Clarke’s approach to reflexive thematic analysis. *Quality & Quantity*, *56*(3), 1391–1412. https://doi.org/10.1007/s11135-021-01182-y

Dinh, C. T. (2023). IMPACT OF SYNCHRONOUS ONLINE LEARNING ENVIRONMENT ON STUDENTS’ COGNITIVE ENGAGEMENT AND LEARNING OUTCOMES. *Turkish Online Journal of Distance Education*, *24*(3), 21–38. https://doi.org/10.17718/tojde.1165209

Dolasinski, M. J., & Reynolds, J. (2020). Microlearning: A New Learning Model. *Journal of Hospitality & Tourism Research*, *44*(3), 551–561. https://doi.org/10.1177/1096348020901579

Dowker, A., Sarkar, A., & Looi, C. Y. (2016). Mathematics Anxiety: What Have We Learned in 60 Years? *Frontiers in Psychology*, *7*(APR). https://doi.org/10.3389/fpsyg.2016.00508

Emiru, E. K., & Gedefaw, M. T. (2024). The effect of teacher self-efficacy on learning engagement of secondary school students. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186X.2024.2308432

Fredricks, J. A., Parr, A. K., Amemiya, J. L., Wang, M.-T., & Brauer, S. (2019). What Matters for Urban Adolescents' Engagement and Disengagement in School: A Mixed-Methods Study. *Journal of Adolescent Research*, *34*(5), 491–527. https://doi.org/10.1177/0743558419830638

Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., & Hlosta, M. (2019). A large-scale implementation of predictive learning analytics in higher education: the teachers' role and perspective. *Educational Technology Research and Development*, *67*(5), 1273–1306. https://doi.org/10.1007/s11423-019-09685-0

Lateh, A. (2017). Using Project Based Learning in Statistics Course to Develop the Statistical Literacy for College Students. *The Asian Conference on Education 2017 Official Conference Proceedings*.

Legacy, C., Zieffler, A., Fry, E. B., & Le, L. (2022). COMPUTES: DEVELOPMENT OF AN INSTRUMENT TO MEASURE INTRODUCTORY STATISTICS INSTRUCTORS' EMPHASIS ON COMPUTATIONAL PRACTICES. *Statistics Education Research Journal*, *21*(1). https://doi.org/10.52041/serj.v21i1.63

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

Leung, F. K. S. (2021). Jewish culture, Chinese culture, and mathematics education. *Educational Studies in Mathematics*, *107*(2), 405–423. https://doi.org/10.1007/s10649-021-10034-3

Mohammed, G. S., Wakil, K., & Nawroly, S. S. (2020). The effectiveness of microlearning to improve students' learning ability. *International Journal of Educational Research Review*, *5*(4), 340–348. https://doi.org/https://doi.org/10.24331/ijere.756917

Nguyen Tran, H. T., Jou She, W., Kajimura, S., & Shibuya, Y. (2025). Assessing Notification Timing Strategies for Improved Micro-Learning Engagement. *IEEE Access*, *13*(February), 64534–64545. https://doi.org/10.1109/ACCESS.2025.3559521

Nikkhoo, I., Ahmadi, Z., Akbari, M., Imannezhad, S., Ardekani, S. A., & Lashgari, H. (2023). Microlearning for Today's Students: A Rapid Review of Essentials and Considerations. *Med Edu Bull*, *4*(11), 687–699. https://doi.org/10.22034/meb.2022.355659.1066

Rincón-Flores, E. G., Mena, J., Ramírez-Montoya, M. S., & Velarde, R. R. (2020). The use of gamification in xMOOCs about energy: Effects and predictive models for participants' learning. *Australasian Journal of Educational Technology*, *36*(2), 1–17. https://doi.org/10.14742/AJET.4818

Robles, H., Jimeno, M., Villalba, K., Mardini, I., Viloria-Nuñez, C., & Florian, W. (2023). Design of a micro-learning framework and mobile application using design-based research. *PeerJ Computer Science*, *9*, e1223. https://doi.org/10.7717/peerj-cs.1223

Sankaranarayanan, R., Leung, J., Abramenka-Lachheb, V., Seo, G., & Lachheb, A. (2023). Microlearning in Diverse Contexts: A Bibliometric Analysis. *TechTrends*, *67*(2), 260–276. https://doi.org/10.1007/s11528-022-00794-x

Scheffel, Drachsler, H., Toisoul, C., Ternier, S., & Specht, M. (2017). *Data Driven Approaches in Digital Education* (É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (eds.); Vol. 10474). Springer International Publishing. https://doi.org/10.1007/978-3-319-

66610-5

Wang, X., Li, Z., & Xiao, L. (2020). Measuring student engagement in statistics courses. *Journal of Statistics Education*, *28*(2), 154–167. https://doi.org/https://doi.org/10.1080/10691898.2020.1767515