# Statistical evaluation of the impact of microlearning and adaptive teaching algorithms on student performance

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**A R T I C L E I N F O**

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**A B S T R A C T**

*This study examines the impact of combining microlearning, virtual laboratories, and adaptive teaching algorithms on student motivation, engagement, and academic performance in an open and distance learning (ODL) setting. An experimental design involving 61 university students was used, with participants divided into experimental and control groups. The instructional module integrated short-form content, interactive virtual lab tasks, and adaptive strategies. Data were collected via structured questionnaires and academic records from the EMPRO system. Using SPSS, descriptive statistics, T-tests, N-Gain, and ANCOVA were applied. Results showed significant improvements in motivation and academic achievement in the experimental group ($p < 0.05$), while engagement levels remained comparably high across both groups. N-Gain analysis revealed a strong learning gain (0.529) in the experimental group versus 0.112 in the control group. ANCOVA confirmed that the learning gains were primarily due to the intervention itself. Overall, the study supports the effectiveness of a microlearning-based adaptive model in enhancing student outcomes in ODL environments.*

## 1. Introduction

The use of digital technologies in education is one of the key factors transforming the modern teaching process. These technologies serve as vital tools to enhance the quality of education and to make instructional methods more flexible and engaging. The pandemic period accelerated the integration of such technologies into education, enabling students to access learning in more adaptable and inclusive ways. For instance, digital tools such as mobile devices, simulations, and virtual laboratories have led to revolutionary changes in educational systems, opening new opportunities for both students and teachers [1].

At the same time, adaptive teaching strategies help create personalized learning pathways in education. This approach aims to improve students' learning outcomes by tailoring instructional methods to their individual needs. Adaptive learning platforms monitor students’ progress, allowing for the development of more effective and precise teaching plans. In addition, approaches like microlearning and self-regulated learning make the educational experience more engaging and productive for students [2].

Microlearning is a strategy that enables students to engage more efficiently and actively in the learning process. This method focuses on delivering knowledge through short lessons and small topic blocks, which helps capture students' attention and makes learning more effective [3].

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However, the implementation of digital technologies in education also faces certain challenges. It is crucial to ensure better integration of students with educational tools, facilitate teachers' adaptation to these technologies, and align their usage with the education system [4]. Moreover, the development of student assessment systems and the adoption of more predictive, data-driven approaches are essential. Such systems provide teachers with more accurate and objective assessment opportunities, enabling more effective evaluation of student performance [5].

## 2. Problem statement

The main aim of this study is to evaluate the impact of microlearning and adaptive teaching algorithms on student performance in a statistically grounded and educationally relevant context. Microlearning and adaptive teaching approaches have begun to find wide application in educational systems. These methods enable a more efficient and effective learning process by addressing the individual needs of students. However, comprehensive assessments of their impact on student performance and detailed analyses of how these methods are integrated into the educational environment are still limited.

Firstly, the effects of microlearning on student satisfaction and learning effectiveness have not been sufficiently clarified. While microlearning—with its short and focused lessons—can enhance student motivation, there is a lack of statistical analyses and empirical studies that demonstrate the long-term effects of this approach on academic performance. Similarly, how adaptive teaching promotes academic progress and its specific role in the instructional process require deeper investigation [6].

Although these approaches may enhance student performance, further models and multivariate statistical analyses are needed to uncover how this improvement is related to specific components of the intervention. For instance, factors such as students' self-regulated learning skills, attitudes towards technology, and the amount of time allocated to instructional modules may influence learning outcomes.

To objectively measure the improvement in student performance through microlearning and adaptive systems, multi-level approaches, cross-validated learning assessments, and continuous monitoring mechanisms over time should be implemented.

Moreover, evaluating the practical deployment of these systems must consider technical resource requirements and human factors, such as teachers' workload, technological proficiency, and students' confidence in using these tools.

Additionally, challenges arising from the implementation of these methods in real educational settings must be addressed, and effective strategies must be developed to maximize their benefits. Technological and pedagogical barriers encountered by both teachers and students can hinder the full potential of these approaches. Such barriers may include the improper use of instructional tools, varying learning paces among students, and limitations in available resources and technological infrastructure.

Thus, the central problem is to determine how microlearning and adaptive teaching algorithms enhance student performance, how effective these approaches are in the educational environment, and what strategies should be developed for their broader implementation in education. Addressing this problem can contribute to the advancement of modern educational systems and encourage the development of new strategies aimed at improving student outcomes.

## 3. Methodology

The main objective of this study is to analyze how the integration of a virtual laboratory into a microlearning environment affects students' motivation, engagement, and academic achievement within the context of open and distance learning (ODL) [7,8]. To achieve this goal, statistical analyses and algorithmic methods were employed to evaluate students' learning behaviors and educational outcomes.

An experimental study was conducted involving 61 students. The participants engaged with a specially designed instructional module that combined virtual laboratory activities, microlearning approaches, and adaptive teaching algorithms [9]. While interacting with the module, each student completed various types of tests and surveys aimed at measuring indicators such as motivation, engagement, and academic success.

To assess the impact of microlearning on student motivation and engagement in an ODL setting, a comparative analysis was carried out between two distinct groups: an experimental group and a control group. Table 1 presents a summary of the case processing and data handling involved in the experiment.

An important point regarding the reliability and validity of the study is that no missing or incomplete data were recorded in either group. The results of all 29 students in the experimental group and 32 students in the control group were fully collected. This completeness of data enhances the statistical validity of the conducted analyses and increases the generalizability of the results.

**Table 1**

Case Processing Summary

| Group | Valid | Percent (%) | Missing | Percent (%) | Total | Percent (%) |
|---|---|---|---|---|---|---|
| Experiment | 29 | 100.0 | 0 | 0.0 | 29 | 100.0 |
| Control | 32 | 100.0 | 0 | 0.0 | 32 | 100.0 |

In this study, data were collected using custom-designed questionnaires specifically developed for the research. The questionnaires included both open-ended and closed-ended questions and were structured to assess the following aspects of student performance:

- Motivation level: Questions were designed to measure students' interest in the course, level of active participation, and attitudes toward educational technologies.
- Engagement and activeness: Questions aimed to determine how actively students participated in lessons and learning activities.
- Academic achievement: All outcomes were obtained from the EMPRO academic management system, which recorded each student's final score out of 100.

The collected data were analyzed using the SPSS software package, which is widely used for both descriptive and inferential statistical analyses. In this study, SPSS was employed to analyze student motivation, engagement, and academic achievement.

Preliminary data on students' motivation and engagement were analyzed using descriptive statistics. This method enabled the examination of the overall distribution of scores, including means, medians, and standard deviations. The analysis was employed to assess general student behavior and to identify potential trends within the data.

The following statistical methods were used to measure students' motivation and engagement, as well as to evaluate their influence on academic achievement:

- T-test: This method was used to determine whether the differences in students' motivation and engagement were statistically significant.

- N-Gain: Applied to measure the improvement between students' initial knowledge levels and their post-intervention results. This approach was utilized to evaluate academic achievement.
- ANCOVA (Analysis of Covariance): This method was used to assess the effect of the new intervention on academic outcomes, while controlling for students' prior performance and motivation levels.

The study has certain limitations. For example, it was conducted solely with students from a single university, which may limit the generalizability of the results to other educational institutions. Additionally, individual differences among students and their prior learning experiences were not fully taken into account, which may introduce some limitations in the interpretation of the findings.

The analysis began with descriptive statistics, T-tests, N-Gain, and Analysis of Covariance (ANCOVA). The data collected from questionnaires and tests were organized into tables and visualized through charts to better illustrate distribution patterns and trends. This analysis provided insights into how students' motivation and engagement levels changed during the intervention period. Moreover, this section outlines the development of students' academic performance before and after the intervention, both in terms of cognitive and practical skills. The results of the descriptive statistics and T-tests played a crucial role in identifying significant trends and changes throughout the study, helping the researcher to better understand the impact of the virtual laboratory on students' motivation and engagement, particularly within the context of microlearning in ODL (open and distance learning) environments.

Finally, the improvement in academic achievement across groups was tested using N-Gain analysis, while ANCOVA was applied to ensure the validity of the experiment and to control for the influence of covariates and other external variables.

## 4. Results

This section presents the findings from the analysis conducted on 61 students. The analysis began with descriptive statistics, followed by T-tests, N-Gain calculations, and ANCOVA. The results were interpreted using tables, graphs, and statistical formulas to comprehensively illustrate the changes in students' motivation, engagement, and academic achievement.

Mean score – this indicator reflects the overall performance level of students. It represents the average value of students' motivation and engagement, providing a general measure of how actively and consistently they participated.

Standard deviation (s) indicates the degree to which students' individual scores deviate from the group's mean score—that is, the variability or spread of the data. The smaller the standard deviation, the more consistent and stable the results are.

The standard deviation is calculated using the following formula:

$$s = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (1)$$

where $s$ is the standard deviation; n is the total number of observations; $x_i$ is the value of the $i^{th}$ observation; $\bar{x}$ is the mean of the observations.

In this study, for the experimental group we had $n$ = 29 students, with individual motivation scores $x_i$ ranging from 72.5 to 90.0 points. The sample mean was $\bar{x} =$ 86.08. Substituting the values into the formula (1):

$$s = \sqrt{\frac{1}{29-1}\sum_{i=1}^{29}(x_i - 86.08)^2} = 4.58$$

The range represents the difference between the highest and lowest values in a dataset. It reflects the overall spread or dispersion of the data distribution.

In accordance with standard statistical reasoning [10], confidence intervals were used to generalize the findings from the sample to the broader population, accounting for sampling variability. The confidence interval (CI) estimates the range in which the true population mean is likely to fall, with 95% certainty. A narrower interval indicates more reliable and consistent results.

The formula used is:

$$CI = \bar{x} \pm t_{\alpha/2,df} \times \frac{s}{\sqrt{n}} \tag{2}$$

where $\bar{x}$ – sample mean; $s$ – standard deviation; n – sample size; $t_{\alpha/2,df}$ – critical value from the t-distribution (approximately 2.048 for 95% confidence and df = 28).

Substituting the values into equation (2):

$$CI = 89.73 \pm 2.048 \times \frac{2.79}{\sqrt{29}} = 89.73 \pm 1.06 \Rightarrow [88.67, 90.79]$$

Table 2 provides the key statistical indicators related to the motivation and engagement levels of students in both the experimental and control groups. The analysis revealed that the experimental group had a mean motivation score of 86.08, with a standard deviation of 4.58. The 95% confidence interval for motivation in this group ranged from 84.34 to 87.82. The median value was 85.83, and the range was calculated to be 17.47 points.

In comparison, the control group had a mean motivation score of 75.37, with a standard deviation of 6.83. The 95% confidence interval for the control group was between 72.91 and 77.83. These results indicate a considerably lower level of motivation among students in the control group, supporting the conclusion that the microlearning approach had a positive effect on student motivation.

**Table 2**

Descriptive Statistics for Student Motivation by Group

| Group | Mean | Standard Deviation | Median | Range | Lower Bound 95% CI | Upper Bound 95% CI |
|---|---|---|---|---|---|---|
| Experiment | 86.08 | 4.58 | 85.83 | 17.47 | 84.34 | 87.82 |
| Control | 75.37 | 6.83 | 75.62 | 29.29 | 72.91 | 77.83 |

As shown in Table 3, engagement levels were found to be remarkably high in both groups. The experimental group achieved a mean engagement score of 89.73 (SD = 2.79), while the control group recorded a mean of 90.12 (SD = 3.02). The 95% confidence intervals for the engagement scores were [88.67, 90.79] for the experimental group and [89.03, 91.20] for the control group. These results demonstrate that both groups had high engagement levels, with no statistically significant difference observed in this variable.

**Table 3**

Descriptive Statistics for Student Engagement by Group

| Group | Mean | Standard Deviation | Median | Range | Lower Bound 95% CI | Upper Bound 95% CI |
|---|---|---|---|---|---|---|
| Experiment | 89.73 | 2.79 | 90.30 | 9.20 | 88.67 | 90.79 |
| Control | 90.12 | 3.02 | 91.38 | 8.95 | 89.03 | 91.20 |

According to the data presented in Table 4, academic performance scores were collected from the EMPRO academic management system, with a maximum of 100 points for each student. All students received complete and valid scores. The descriptive analysis revealed that academic achievement was notably higher in the experimental group compared to the control group. The experimental group achieved a mean score of 85.5 (SD = 4.91), while the control group recorded a mean of 66.5 (SD = 5.80). The 95% confidence intervals for academic achievement were [83.81, 87.19] for the experimental group and [64.55, 68.45] for the control group.

**Table 4**

Descriptive Statistics for Academic Achievement by Group

| Group | Mean | Standard Deviation | Median | Range | Lower Bound 95% CI | Upper Bound 95% CI |
|---|---|---|---|---|---|---|
| Experiment | 85.5 | 4.91 | 85.93 | 20.55 | 83.81 | 87.19 |
| Control | 66.5 | 5.8 | 66.32 | 25.42 | 64.55 | 68.45 |

The results reveal a statistically significant difference in academic performance between the experimental and control groups, with students in the experimental group achieving higher average scores and more consistent results. Academic performance data, retrieved from the EMPRO academic management system, confirm that the integration of microlearning modules positively influenced learning outcomes. While engagement levels were high across both groups, the experimental group exhibited slightly lower variability, indicating a more stable participation pattern under the microlearning framework.

In contrast, motivation levels showed a pronounced difference in favor of the experimental group. Higher mean scores, tighter confidence intervals, and a narrower range suggest that the microlearning approach was particularly effective in enhancing student motivation. Taken together, these findings support the conclusion that microlearning not only sustains student engagement but also contributes significantly to motivation and academic success in open and distance learning environments.

While the descriptive statistics provided an initial overview of the differences in motivation, engagement, and academic achievement between the experimental and control groups, they do not by themselves determine whether these differences are statistically significant. To validate the observed effects of the microlearning-based intervention, it is essential to apply inferential statistical methods.

Therefore, the next phase of the analysis involves the application of T-tests, Normalized Gain (N-Gain) calculations, and Analysis of Covariance (ANCOVA).

To determine whether there were statistically significant differences between the experimental and control groups in terms of motivation, engagement and academic achievement, an independent samples T-test was conducted for each variable. The T-test is used to assess whether the means of two independent groups differ significantly from one another [11]. In this context, a p-value of less than 0.05 was considered statistically significant.

$$t = \frac{(\overline{X_1} - \overline{X_2})}{\sqrt{\frac{{S_1}^2}{n_1} + \frac{{S_2}^2}{n_2}}} \tag{3}$$

Where $\overline{X_1} and\ \overline{X_2}$ are the sample means of the first and second groups, respectively; $s_1$ and $s_2$ are the standard deviations of the two groups; $n_1$ and $n_2$ are the number of participants in groups.

Then, taking into account expression (3): $\overline{X_1} = 86.08,\ s_1 = 4.58,\ n_1 = 29\ (experimental\ group); \overline{X_2} = 75.37, s_2 = 6.83, n_2 = 32\ (control\ group).$

$$t = \frac{(86.08 - 75.37)}{\sqrt{\frac{4.58^{\,2}}{29} + \frac{6.83^{\,2}}{32}}} \approx 7.251$$

Since p < 0.0001, the difference in motivation is statistically significant. Using Equation (3), the calculated t-statistic for engagement was –0.518, with a p-value of 0.6061. Since p > 0.05, no statistically significant difference in engagement was found between the two groups. This suggests that while both groups demonstrated high levels of participation, the microlearning approach did not produce a distinct impact on engagement.

According to Equation (3), the t-test conducted for academic achievement resulted in a t-value of 13.29 and a p-value < 0.0001. This indicates a statistically significant difference in academic performance between the experimental and control groups, with the experimental group outperforming the control group, further supporting the effectiveness of microlearning.

Table 5 summarizes the results of independent samples T-tests conducted to compare the experimental and control groups across three key parameters: motivation, engagement, and academic achievement. The table presents the t-statistics, corresponding p-values, and whether each difference was statistically significant at the 0.05 level.

**Table 5**

Independent Samples T-Test Results

| **Parameter** | **t-statistic** | **p-value** | **Statistically significant (p<0.05)** |
|---|---|---|---|
| Motivation | 7.251 | 0.0000 | Yes |
| Engagement | -0.518 | 0.6061 | No |
| Academic achievement | 13.290 | 0.0000 | Yes |

To further evaluate students' learning gains, an N-Gain analysis was conducted based on pre-test and post-test results. This method was used to assess academic achievement by calculating the improvement between a student's initial knowledge level and their subsequent performance, normalized over the maximum possible improvement. The following formula was applied:

$$N - Gain = \frac{Post - Pre}{100 - Pre} \tag{4}$$

The experimental group achieved an average N-Gain score of 0.529, while the control group scored 0.112 (Fig. 1). This substantial difference indicates that the integration of the virtual laboratory within the microlearning environment had a positive impact on students' academic achievement.

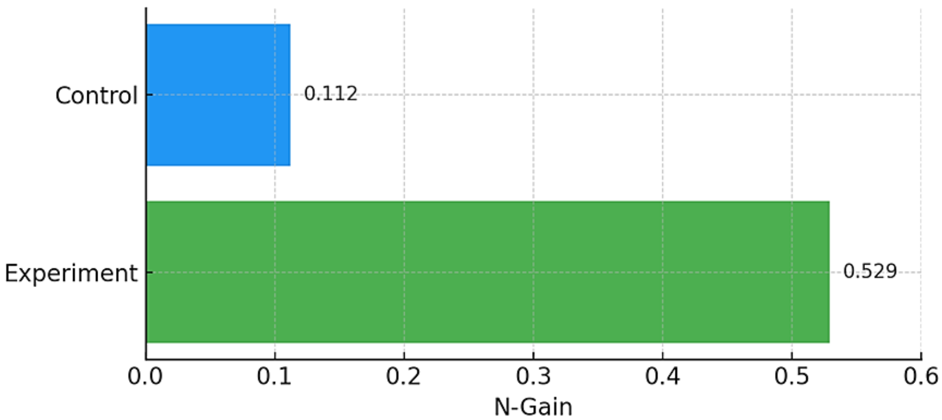


**Fig. 1.** Mean N-Gain Scores by Group

**Table 6**

N-Gain Analysis Results

| Group | Pre-test Score | Post-test Score | N-Gain (Mean) |
|---|---|---|---|
| Experimental | 50.2 | 85.5 | 0.529 |
| Control | 48.5 | 66.5 | 0.112 |

In the next phase of the analysis, Analysis of Covariance (ANCOVA) was employed to evaluate the effects of both pre-test scores and group membership (experimental vs. control) on the post-test outcomes. This method serves the following key purposes:

- To compare the post-test performance between the two groups while statistically controlling for initial differences in pre-test scores;
- To isolate and assess the net effect of the intervention (i.e., the microlearning-based instructional method) on student outcomes.

The ANCOVA model used in this study can be expressed as follows:

$$Post - test = \beta_0 + \beta_1(Group) + \beta_2(Pre - test) + \epsilon \tag{5}$$

Where $\beta_0$ is the intercept; $\beta_1$ represents the effect of group (experimental vs. control); $\beta_2$ accounts for the influence of pre-test scores; $\epsilon$ is the random error term.

The results of the ANCOVA analysis indicated that the group factor had a statistically significant effect on post-test performance ($p < 0.05$). This confirms that the instructional approach, specifically the integration of microlearning, contributed to a meaningful difference in academic achievement between the experimental and control groups. Additionally, the analysis showed that pre-test scores, used as a covariate, did not significantly influence post-test outcomes ($p = 0.357 > 0.05$), suggesting that initial performance levels did not bias the results.

The F-statistic in ANCOVA is calculated using the following formula:

$$F = \frac{MS_{between}}{MS_{within}} = \frac{SS_{between}/df_{between}}{SS_{within}/df_{within}} \tag{6}$$

Where $SS_{between}$ – sum of squares for the factor or covariate (e.g., between groups or pre-test); $df_{between}$ – degrees of freedom for the factor or covariate; $SS_{within}$ – residual (within groups) sum of squares; $df_{within}$ – residual (within groups) degrees of freedom; MS – mean square.

Based on equation (6), the F-statistic was calculated to assess the significance of the effect.

$$F = \frac{2190.37/1}{1799.75/58} = 70.59$$

A breakdown of the ANCOVA output is presented in Table 7, where the "Between Groups" source yielded an F-statistic of 70.59 and a corresponding p-value of 0.000, indicating a strong statistical difference between groups. The "Covariate (Pre)" source, however, had an F-statistic of 0.86 with a p-value of 0.357, thus not reaching the threshold for statistical significance. The "Within Groups" variance represents residual variability due to individual differences and measurement error.

These results provide robust evidence that the observed improvement in academic performance was largely attributable to the intervention itself—namely, the microlearning-enhanced instructional model—rather than to pre-existing differences in students' prior knowledge. Thus, the microlearning approach not only improved average outcomes but also significantly influenced students' learning progression, underscoring its effectiveness in fostering deeper and more equitable academic development.

**Table 7**

ANCOVA Test Results

| Source | Sum of Squares | df | F-value | p-value |
|---|---|---|---|---|
| Between Groups | 2190.3673 | 1 | 70.5884 | 0.000 |
| Covariate (Pre) | 26.7564 | 1 | 0.8623 | 0.357 |
| Within Groups | 1799.7463 | 58 | - | - |

- Since the p-value for the Between Groups factor is 0.000 < 0.05, there is a statistically significant difference in post-test scores between the experimental and control groups.
- In contrast, the p-value for the Covariate (Pre-test) is 0.357 > 0.05, indicating that the initial knowledge level had no statistically significant effect on the post-test results.

These findings confirm that the microlearning-based intervention significantly improved students' academic outcomes, not only in terms of average performance but also in terms of individual learning progression and consistency.

## 5. Conclusion

Based on the statistical analyses conducted, the effectiveness of the microlearning-based instructional approach was validated by three key indicators: motivation, engagement, and academic achievement. According to T-test and ANCOVA results, the microlearning approach significantly enhanced students' motivation and academic performance. Although engagement levels remained high in both groups, no statistically significant difference was observed in this parameter.

The N-Gain analysis further confirmed the learning gains achieved by the experimental group, while ANCOVA results validated that the observed improvements were attributed primarily to the intervention itself rather than initial knowledge levels. Thus, the proposed microlearning-enhanced model proves to be effective not only for individual skill development but also for comparative assessment of instructional methods in open and distance learning environments. Nevertheless, since the study was conducted within a single institution, the generalizability of the findings to other educational settings may be limited.

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