



A Comparative Analysis of Learning Outcomes in Online and In-Person Courses for College Students in East Java

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ABSTRACT

This study aims to compare students' experiences and perceptions of learning outcomes in online and offline courses based on survey data from 150 respondents. The analysis includes five paired metrics duration of focus, percentage of material understood, number of notes taken, effectiveness rating, and assignment volume rating, as well as five categorical preference questions. The Shapiro–Wilk test was applied to the differences between offline and online scores to assess normality. Since all metrics yielded p-values below 0.05, differences in numerical metrics were analyzed using the Wilcoxon signed-rank test. Categorical preferences were analyzed using the exact binomial test against a reference proportion of 50%, while the p-values for all ten tests were corrected using the Holm-Bonferroni method. K-Means clustering was applied to the five standardized offline-online difference features. The results show that the offline group had significantly higher medians for focus duration, comprehension percentage, number of notes, and effectiveness ratings, while task volume ratings did not differ significantly after Holm's correction. Preference for the offline method was also dominant in terms of preferred method, most effective method, ease of discussion, and impact on health; preferences regarding scheduling did not show significant dominance. Segmentation yielded two clusters consisting of 81 and 69 respondents, respectively. These results illustrate patterns within the survey sample and do not, by themselves, represent all students in East Java.

Keywords: *online classes, in-person class es, Shapiro–Wilk, Wilcoxon, K-Means Clustering*

I. Introduction

Advances in information technology have brought about changes in the delivery of educational activities, including the teaching process at universities. Learning activities that were previously conducted primarily in person in classrooms can now also be carried out online through various digital platforms. These two learning methods have distinct characteristics. Online classes make it easier for students to access course materials from various locations, while in-person classes allow students to interact directly with instructors and their peers. These differences can influence students' experiences during lectures, whether in terms of comfort, engagement in learning, or how they comprehend the material presented.

Students' experiences in attending classes can be assessed through several aspects, such as duration of focus, percentage of material comprehension, number of notes taken, evaluation of learning effectiveness, and perception of the volume of assignments. In online classes, students have the flexibility to choose where and when to study, but their learning experience can also be influenced by environmental conditions and the facilities used. Meanwhile, in-person classes provide students with the opportunity to ask questions directly, engage in discussions, and receive additional explanations when they have difficulty understanding the material. However, each student may have a different experience with these two methods. Therefore, a comparison must be made by considering several aspects so that the results of the analysis can provide a more comprehensive picture.

Research on online and offline learning has been conducted in various educational contexts. Indriyanti, Sudarti, and Handayani [1] discuss a comparison of student learning outcomes in online and offline learning. Other studies examine the implementation of courses, learning outcomes, and

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student motivation in both learning methods [2], [3]. Furthermore, a literature review on online and offline learning in Indonesia also indicates that comparisons of the two methods must take into account the context in which learning takes place [4]. These studies serve as the foundation for examining students' experiences with both teaching methods. In this study, comparisons were made using five numerical metrics and five preference aspects so that differences in student evaluations could be observed from multiple perspectives.

Previous research has compared online and in-person classes, but three questions remain largely unanswered. First, most of the studies mentioned above assessed a single aspect (learning outcomes or motivation) within a single academic program, college, or city. Second, student preferences regarding non-academic aspects—such as ease of discussion, time management, and health—are rarely analyzed alongside learning indicators among the same respondents. Third, no studies have yet examined whether students can be grouped based on distinct patterns of assessment differences while controlling for errors resulting from multiple simultaneous tests. Furthermore, perceptions of learning outcomes need to be distinguished from measurable learning achievements, as the two do not always align [5], [6].

The contributions of this study are as follows. To address this gap, this study makes three contributions: (1) comparing five indicators of perceptions of online and offline learning among 150 students from eight faculties using the Wilcoxon signed-rank test and effect sizes; (2) analyzing preferences across five aspects—including discussion, time management, and health—using the exact binomial test with Holm's correction; and (3) conducting an exploratory cluster analysis using K-Means to determine whether patterns of rating differences vary across groups. The purpose of this study is to analyze differences in students' perceptions of online and in-person classes based on survey data from 150 respondents. Since the data comes from a survey, the results are interpreted as the respondents' reports and do not prove a cause-and-effect relationship or represent all students in East Java.

II. METHODS

A. Data

The data used in this study consists of primary data obtained by distributing a questionnaire via Google Forms to students. The questionnaire was distributed via WhatsApp and yielded 150 responses. The research variables included preferred learning methods, duration of concentration, percentage of material comprehension, number of notes taken, and assessments of the effectiveness and workload of online and offline learning. The variables used in this study are presented in Table I.

Table I. Research Variables

No.	Variable	Description	Data Type
1.	Preferred Learning Methods	The learning method most preferred by respondents	Categorical
2.	The Most Effective Method	Teaching methods that respondents considered most effective	Categorical
3.	The Easiest Method for Discussion	The teaching method considered most conducive to discussion	Categorical
4.	The Best Methods for Time Management	The learning method considered to make time management easiest	Categorical
5.	Health-Influencing Methods	Learning methods that are considered to have an impact on health	Categorical
6.	Online Focus Duration	How long students can stay focused during online learning	Numeric
7.	Offline Focus Duration	The length of time students can stay focused during in-person classes	Numeric
8.	Percentage of Online Learners	Percentage of students' understanding of the material during online learning	Numeric

9.	Percentage of Offline Understanding	Percentage of students' understanding of the material during in-person classes	Numeric
10.	Number of Online Entries	The number of notes taken by students during online classes	Numeric
11.	Number of Offline Entries	The number of notes taken by students during in-person classes	Numeric
12.	Online Effectiveness Rating	Students' Assessments of the Effectiveness of Online Learning	Categorical
13.	Offline Effectiveness Rating	Students' Assessments of the Effectiveness of In-Person Learning	Categorical
14.	Online Assignment Volume Rating	Students' Perceptions of the Volume of Assignments in Online Learning	Categorical
15.	Offline Assignment Volume Rating	Students' Assessments of the Volume of Assignments in In-Person Learning	Categorical

B. Data Collection

The research data was collected from 150 students via a Google Forms questionnaire between September 2 and 15, 2026. The questionnaire link was shared via WhatsApp (class groups, organization groups, and direct messages), so the selection of respondents was based on convenience sampling (non-probability). The questionnaire contained 15 questions that took about five minutes to complete, and respondents filled it out voluntarily.

Respondents came from eight faculties: Computer Science, Architecture and Design, Social and Political Sciences, Economics and Business, Agriculture, Medicine, Law, and Engineering and Science. Respondent characteristics: Of the 150 respondents, 131 (87.3%) were from UPN "Veteran" East Java and 19 (12.7%) from seven other universities (University of Jember 8, Surabaya State University 5, Muhammadiyah University of Malang 2, and one each from the Sepuluh Nopember Institute of Technology, Surabaya State Maritime Polytechnic, 17 August 1945 University of Surabaya, and Madura University). Faculty distribution: Computer Science 42, Engineering and Science 17, Architecture and Design 16, and 15 each for Agriculture, Economics and Business, Social and Political Sciences, Law, and Medicine. A total of 113 out of 131 respondents from UPN "Veteran" East Java (86.3%) are students from the class of 2025–2026.

The data collected includes students' evaluations of online and in-person learning based on ten predetermined indicators. This data was used to compare evaluations of the two learning methods, analyze student preferences, and identify patterns of variation in evaluations among students.

C. Data Analysis Techniques

Data analysis was conducted using descriptive statistics, normality tests, difference tests, preference analysis, and data clustering. Descriptive statistics were used to describe the characteristics of the data and the trends in respondents' evaluations of online and offline learning.

The normality test was performed using the Shapiro-Wilk test [7] to determine whether the data on the differences in ratings between offline and online learning were normally distributed. Next, the Wilcoxon Signed-Rank test was used to determine whether there were significant differences between the two learning methods [8], [9]. Decision-making was based on the p-value at a 5% significance level. A p-value below 0.05 indicates sufficient statistical evidence to conclude a significant difference, while a p-value equal to or above 0.05 indicates that the statistical evidence is insufficient to conclude a significant difference. The Holm correction was applied [10] to adjust for testing across five indicators and to control the risk of error due to repeated testing.

A preference analysis was conducted to determine students' preferences regarding online versus offline learning. Next, all ten p-values (five Wilcoxon and five binomial) were corrected using the Holm-Bonferroni method. A 5% significance level was applied to the corrected p-values.

K-means clustering [11], [12] was performed on five features representing the differences between offline and online learning, which were standardized using StandardScaler to ensure that differences in scale did not dominate the distances. The number of clusters (K) was tested within the range of 2–7 and selected by considering the elbow (inertia) method and the silhouette coefficient [13]. The interpretation of the silhouette coefficient follows Kaufman and Rousseeuw [14]: a value below 0.25 indicates no substantial cluster structure. The stability of the solution against random initialization was assessed using the Adjusted Rand Index (ARI) [15] across trials. Principal component analysis (PCA) was used solely for visualization.

Overall, this study was conducted in several stages, ranging from data collection, data processing, and statistical testing to drawing conclusions. These research stages are presented in Figure 1.

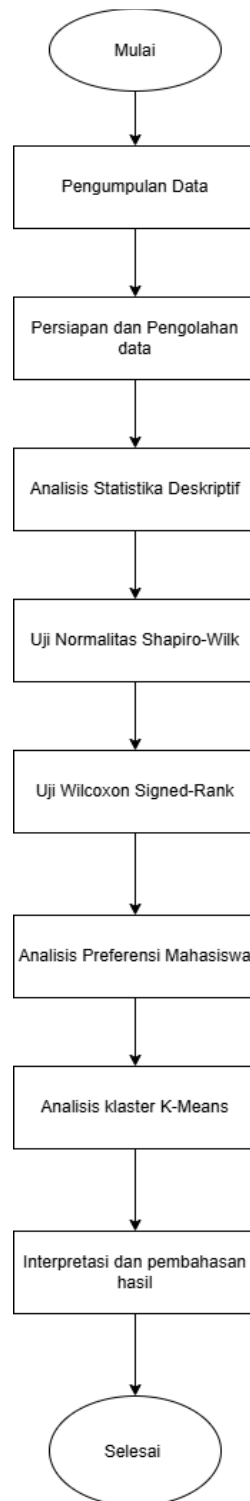


Figure 1. Flowchart

III. RESULTS AND DISCUSSION

A. Data Overview and Descriptive Statistics

Table 1 compares the five indicators. In terms of focus duration, the average for in-person classes (83.8 minutes) far exceeded that of online classes (50.8 minutes), and the range for in-person

classes was much wider, extending up to 180 minutes. Students estimated their understanding of the material at 85.0% for in-person classes and 61.8% for online classes. The number of notes per session increased from 1.47 pages (online) to 3.00 pages (offline), and the learning effectiveness rating rose from 2.82 to 4.41. The only indicator that appeared similar was the volume of assignments (3.52 for online and 3.71 for offline). The standard deviation (SD) for in-person classes was higher for focus duration and notes, indicating that the in-person experience varied more widely among respondents.

Table II. Results of the normality test for the difference between offline and online scores.

Indicators	Online: mean $\pm$ SD	Online: median (Q1–Q3)	Offline: mean $\pm$ SD	Offline: median (Q1–Q3)
Duration of focus	50.77 $\pm$ 20.51	60.0 (30.0–60.0)	83.84 $\pm$ 40.09	67.5 (60.0–120.0)
Percentage of understanding	61.83 $\pm$ 16.56	60.0 (50.0–75.0)	84.95 $\pm$ 6.84	85.0 (80.0–90.0)
Number of notes	1.47 $\pm$ 0.85	1.0 (1.0–2.0)	3.00 $\pm$ 1.26	3.0 (2.0–4.0)
Effectiveness rating	2.82 $\pm$ 0.69	3.0 (2.0–3.0)	4.41 $\pm$ 0.60	4.0 (4.0–5.0)
Workload rating	3.52 $\pm$ 0.91	3.0 (3.0–4.0)	3.71 $\pm$ 0.82	4.0 (3.0–4.0)

The average difference between offline and online performance was significant across four indicators: focus duration of 33.1 minutes (83.84 vs. 50.77), comprehension percentage of 23.1 percentage points (84.95 vs. 61.83), number of notes: 1.53 pages (3.00 vs. 1.47), and effectiveness rating: 1.59 points (4.41 vs. 2.82). For task volume, the difference was only 0.19 points (3.71 vs. 3.52), and the medians for both groups were in the 3–4 range. The offline data showed greater variation in focus duration (40.09 vs. 20.51) and number of notes (1.26 vs. 0.85), indicating that in-person experiences varied more widely among respondents. Conversely, offline comprehension was highly uniform (SD 6.84; median 85.0) compared to online (SD 16.56), meaning that nearly all respondents felt they understood the material well during in-person classes, whereas perceptions of comprehension during online classes varied widely.

B. Normality Tests and Tests of Differences

The Shapiro-Wilk test on the offline–online differences rejected the assumption of normality for all indicators ($p < 0.001$ for each indicator; W between 0.908 and 0.964). Furthermore, all indicators consisted of discrete values (minutes, percentages, counts, or ratings) with many tied values. Therefore, the Wilcoxon test was used instead of the paired t -test. The results in Table 3 show that offline scores were higher on four indicators with a Holm-corrected p -value < 0.001 : duration of focus ($r = 0.88$), understanding of the material ($r = 0.99$), number of notes ($r = 0.94$), and learning effectiveness ($r = 0.99$). The direction of the results was nearly uniform: for material comprehension, 139 out of 142 respondents with a non-zero difference rated the offline method higher, and for learning effectiveness, 134 out of 136 did so.

Table III. Results of the Normality and Wilcoxon Tests

Indicators	W Shapiro-Wilk	Offline > online	Offline < online	Same	W Wilcoxon	r	Corrected p
Duration of focus	0.949	109	13	28	442.5	0.88	< 0.001
Percentage of understanding	0.964	139	3	8	33.0	0.99	< 0.001
Number of notes	0.939	115	8	27	228.0	0.94	< 0.001

Effectiveness rating	0.908	134	2	14	58.0	0.99	< 0.001
Workload rating	0.935	53	37	60	1593.0	0.22	0.118

Table III shows that offline learning was perceived as superior on four indicators with a Holm-corrected p -value < 0.001 and large effect sizes: duration of focus ($r = 0.88$), understanding of the material ($r = 0.99$), number of notes taken ($r = 0.94$), and learning effectiveness ($r = 0.99$). The direction of the results was nearly uniform: for material comprehension, 139 out of 142 respondents with a non-zero difference rated offline learning higher, and for learning effectiveness, 134 out of 136 did so. There was no significant difference in task volume ($r = 0.22$; corrected $p = 0.118$): 53 respondents rated offline tasks as more intensive, 37 rated online tasks as more intensive, and 60 rated them as equal.

In practical terms, respondents reported being able to maintain focus for about 33 minutes longer, feeling they understood the material by about 23 percentage points more, taking about 1.5 pages more notes, and rating effectiveness about 1.6 points higher during offline classes (average differences in Table II). These differences are significant and consistent in direction, but they represent reported differences in experience, not measurable differences in learning outcomes. Thus, these results are best interpreted as an indication that the students in the sample felt more engaged and better supported during in-person classes.

The discussion of these results must be distinguished from objective evidence. A meta-analysis of measurable learning outcomes found no advantage for face-to-face instruction [5], whereas this study, in contrast, documented a significant advantage for offline instruction in terms of perception. The two are not contradictory: self-assessment is more closely related to affective reactions than to actual cognitive learning [6], and the quality of the online course design experienced by the respondents was not measured, even though well-designed online learning differs from emergency transitions [16]. The offline advantage in focus duration aligns with findings from a local study indicating that in-person instruction is perceived as better at maintaining focus [17]. One explanation—still hypothetical—is the cognitive load of video-based interactions, such as close-up eye contact and constant self-monitoring [18]. It should also be noted that the popular claim about students' attention span waning after 10–15 minutes lacks a strong evidence base, and attention varies depending on the teaching method [19]; the difference in focus duration here is more accurately interpreted as a difference in reported experiences, rather than as a limit to attention capacity. Regarding task volume, there was no significant difference after correction ($r = 0.22$; corrected $p = 0.118$): 53 respondents rated the offline task as more demanding, 37 rated the online task as more demanding, and 60 rated them as equally demanding.

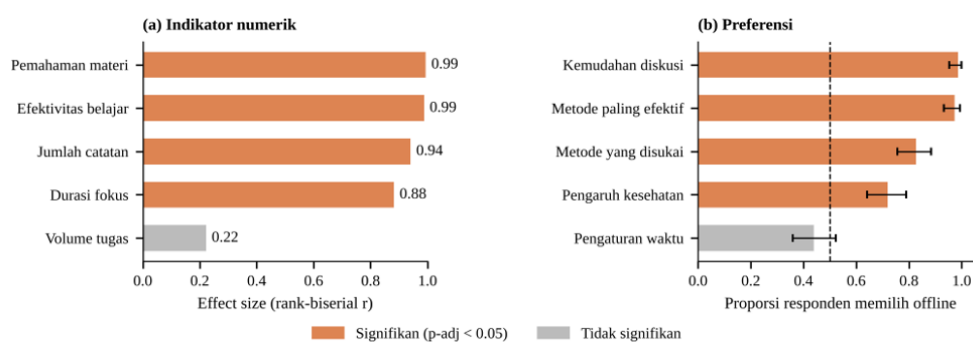


Figure 2. (a) The rank-biserial r effect size for the Wilcoxon test (a positive value indicates that “offline” is higher). (b) The proportion of respondents who chose “offline,” with a 95% confidence interval; the dashed line marks the proportion of 0.5.

C. Student Preferences

In the preference questions, the offline option dominated in four out of five aspects. A total of 124 out of 150 respondents chose offline as their preferred learning method; 146 chose offline as the most effective method; and 148 chose offline as the easiest method for discussion. Regarding the aspect of methods considered to have an impact on health, 108 respondents chose offline. Conversely, regarding time management, 84 respondents chose online and 66 chose offline; this difference in proportions was not significant according to the binomial test after Holm's correction.

Table IV. Distribution of responses and results of the exact binomial test. Percentages are calculated

based on 150 responses.

Preference aspects	Offline	Online	Holm-corrected p	CI 95%
Preferred method	124 (82.7%)	26 (17.3%)	< 0.001	0.756–0.884
Most effective method	146 (97.3%)	4 (2.7%)	< 0.001	0.933–0.993
Easiest for discussion	148 (98.7%)	2 (1.3%)	< 0.001	0.953–0.998
Best for time management	66 (44.0%)	84 (56.0%)	0.165	0.359–0.523
Affects health	108 (72.0%)	42 (28.0%)	< 0.001	0.641–0.790

This pattern is consistent with post-pandemic studies that identify flexibility as the primary reason for choosing online learning and human interaction as the primary reason for choosing in-person learning [20], as well as with local studies reporting time savings [21] and scheduling flexibility [17] in online learning. What is interesting is that the advantage of online learning in terms of time management is not strong enough to alter the overall assessment: students seem willing to trade flexibility for focus, understanding, and interaction. Regarding health, this study did not measure respondents' reasons, so explanations such as physical activity or social interaction are merely hypotheses that need to be tested. Since the question offered only two options, the proportions above cannot distinguish between respondents who truly had no preference and those who were forced to choose.

D. Respondent Segmentation Using K-Means

Cluster analysis was used to determine whether respondents could be divided into groups with different patterns of offline-online differences. The input consisted of five standardized differences from 150 respondents. The results are exploratory and should be interpreted with caution, as the quality of the clusters turned out to be poor.

Inertia decreased smoothly from 587.3 ($K = 2$) to 349.4 ($K = 7$) without any distinct inflection points, while the highest silhouette coefficient was achieved at $K = 2$ (0.188) and all values fell within the range of 0.164–0.188 (Figure 3). Since all values are below 0.25, the data lack a substantial cluster structure [15]. The two principal components of PCA explain only 52% of the variance; therefore, the two-dimensional projection is not used as evidence of cluster separation. The $K = 2$ solution was retained because it is the easiest to interpret and highly stable with respect to initialization (average ARI of 0.995; minimum 0.973). Thus, the clusters are interpreted as an exploratory partition of a continuum of gaps, rather than as distinctly separate groups.

All silhouette values are below 0.25, indicating that the data lack a substantial clustering structure [14]. The two principal components of PCA explain only 52% of the variance (32.7% and 19.7%), and in the projection, the two clusters overlap without a clear boundary (Figure 4); therefore, this figure is not used as evidence of separation. A high ARI merely indicates that the algorithm is consistent; consistency does not equate to the presence of natural clusters, since even truly continuous data can be partitioned consistently.

Therefore, the two clusters are interpreted as an exploratory partition of a single continuum of gaps (larger and smaller gaps), rather than two distinctly separate types of students. The clusters are not used to classify individuals or formulate policies.

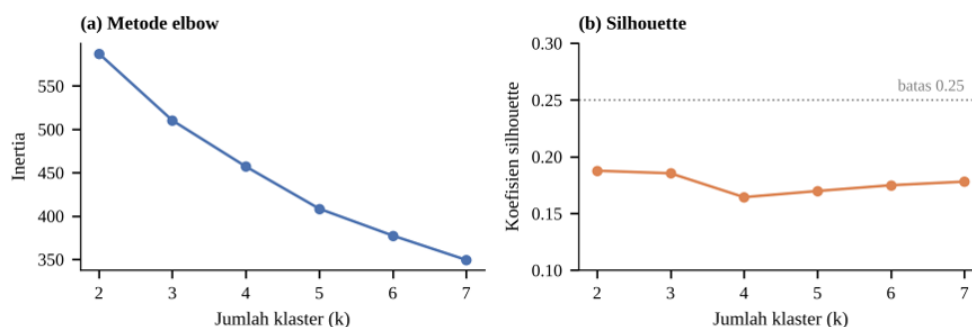


Figure 3. Selection of the number of clusters: (a) inertia using the elbow method and (b) silhouette coefficient; the dashed line marks the 0.25 threshold

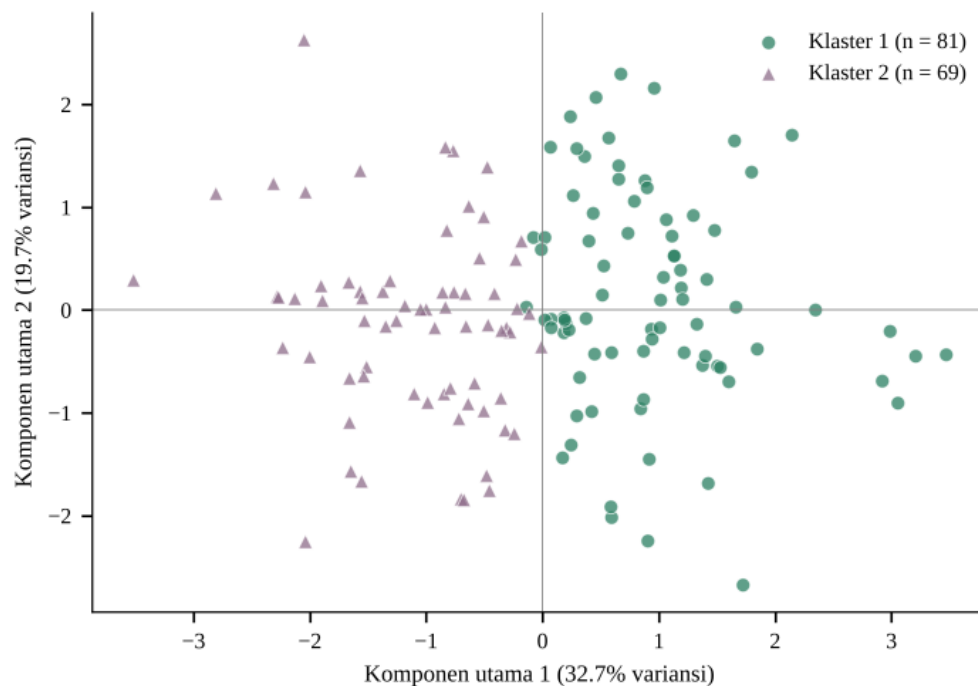


Figure 4. PCA (two principal components) projection of respondents by cluster. The two clusters overlap along principal component 1 without any clear separation..

Cluster 1 consisted of 81 respondents (54.0%) and had the largest gaps: an average offline-to-online difference of 45.6 minutes for focus duration, 30.0 percentage points for comprehension, 2.12 pages of notes, and 2.15 points on the effectiveness rating. Cluster 2 (69 respondents; 46.0%) had smaller differences (18.4 minutes, 15.0 points, 0.84 pages, and 0.93 points) as well as a slightly negative difference in task volume (-0.19), meaning slightly more respondents felt that the online tasks were more demanding (Table V and Figure 5). The differences in these five metrics arose naturally because they were used to form the clusters. More independent evidence can be found in the preference column: in Cluster 1, 92.6% preferred offline and 53.1% chose offline for time management, whereas in Cluster 2 the figures were 71.0% and 33.3%. Thus, both clusters lean toward offline, but Cluster 2 is more open to online, particularly for scheduling (66.7% chose online) and health (59.4% chose offline compared to 82.7% in Cluster 1).

Table V. Profile of the two respondent clusters

Characteristics	Cluster 1	Cluster 2
<i>n</i> (%)	81 (54.0)	69 (46.0)
<i>Average Diference (offline-online)</i>		
Focus duration (minutes)	45.56	18.41
Understanding of material (percentage points)	30.05	15.00
Number of notes (pages)	2.12	0.84
Learning effectiveness (rating points)	2.15	0.93
Assignment volume (rating points)	0.52	-0.19
<i>Percentage of respondents who chose offline</i>		
Preferred method	92.6	71.0
Most effective method	100.0	94.2
Ease of discussion	100.0	97.1

Time management	53.1	33.3
Impact on health	82.7	59.4

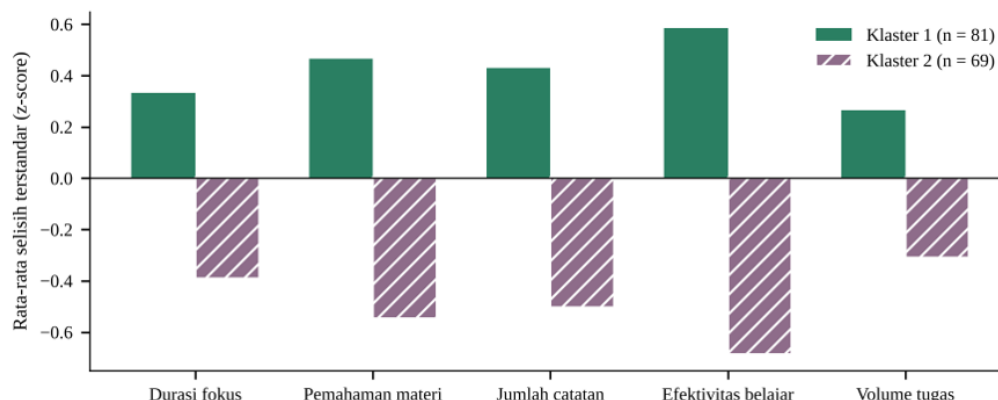


Figure 5. Cluster profiles showing the standardized (z-score) average difference between offline and online scores for the five learning indicators.

These findings suggest that a “one-size-fits-all” policy for all students is not appropriate. Activities that require sustained focus, discussion, and conceptual understanding appear to be better suited for in-person delivery, whereas one-way content or activities that depend on time flexibility can be shifted to an online format. This approach aligns with the advantages of the blended model identified in a meta-analysis [5] and with the recommendations of a local study [17], but our data did not directly test the blended model.

E. Interpretation and Limitations

Overall, the survey data show a trend in which students in the sample reported higher levels of focus, comprehension, note-taking, and effectiveness in in-person classes. The preference results support this pattern, particularly regarding effectiveness and discussion. However, time management is a different matter, as respondents preferred online classes more often; this difference was not significant after multiple corrections.

These findings must be interpreted with several limitations in mind. First, the data comes from a survey and reflects respondents’ reports or assessments, not objective measurements of academic grades or exam results. Second, the available data is insufficient to conclude that the sample is representative of all students in East Java. Third, the silhouette score of 0.188 indicates weak cluster separation, although the algorithm’s stability is relatively high. Fourth, the associations or differences found do not prove that the mode of instruction is a direct cause of changes in learning outcomes.

IV. Conclusion

Based on an analysis of 150 respondents, the Shapiro–Wilk test showed that the offline–online differences across the five metrics were not normally distributed ($p < 0.001$); therefore, numerical comparisons were performed using the Wilcoxon signed-rank test. After Holm’s correction, the offline group had significantly higher medians for focus duration, comprehension percentage, number of notes, and effectiveness rating. Task volume ratings showed no significant differences. The exact binomial test found a dominant preference for offline learning regarding preferred method, most effective method, ease of discussion, and health aspects, while preferences for scheduling did not differ significantly from a 50% proportion.

K-Means produced two clusters: 81 respondents with larger offline–online differences on most metrics and 69 respondents with more moderate differences. However, the highest silhouette score was only 0.188 ($K = 2$), well below the 0.25 threshold for the presence of a substantial cluster structure, and the two clusters overlapped in the PCA projection. Therefore, this segmentation is exploratory in nature: it merely indicates that the degree of the offline–online perception gap varies among respondents (larger among the 81 respondents and smaller among the 69 respondents), not that there are two distinct types of students. These results should not be used to classify individuals or formulate policies, and they need to be confirmed in a larger and more diverse sample. All conclusions apply to the perceptions of the 150 respondents in this sample and are not generalized as objective evidence of academic achievement or as a representation of all students in East Java. Further research is recommended using a more diverse and randomly selected sample, examining the representativeness of the respondents, and combining perceptions with objective academic indicators such as exam scores or final course grades.

APPENDIX

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