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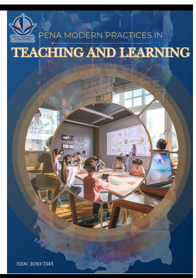

Group Assignment Formation using Cluster Analysis

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ABSTRACT

A group assignment is a task or project that is completed by a group of students (or team members) working together, instead of individually. The traditional method such as random assignment of forming group assignments is by giving students the freedom to choose the members of their own groups. The use of this traditional method can lead to significant variation between groups. Typically, students will choose group members from among their friends who are in the same course, college, or of the same ethnicity, without considering their levels of intelligence. This study delves into the effectiveness of the *K*-means clustering method in forming balanced and high-performing groups for group assignments. The *K*-means clustering method optimizes group formation by grouping individuals into cohesive teams based on skill diversity, compatibility, and task requirements. This study investigates factors influencing group assignment and establishes techniques to enhance clustering-based group formation. The results show that using *K*-means clustering to form group assignment teams can reduce bias and ensure a balanced distribution of key characteristics across teams. This approach also enhances the understanding and engagement of less capable students, thereby improving the overall quality of their learning experience. In conclusion, K-means clustering is suitable for forming group assignments to ensure balance and quality in the work produced.

1. Introduction

The current education system, including in Malaysia, is not solely focused on writing examinations. It encompasses various aspects such as understanding, cognitive skills, communication, entrepreneurship, interpersonal skills, practical skills, digital skills, and teamwork. This is in line with the Malaysia Education Blueprint 2013–2025, as outlined in the second edition of the Malaysian Qualifications Framework (MQF) [1]. This assessment should be practiced at all levels of education, whether in primary and secondary schools, colleges, or higher education institutions.

At the higher education level, such as universities, the skills mentioned above are usually assessed through group assignments. In group assignment, each member must commit to ensuring that the completed task produces an optimal output [2]. In various collaborative settings, such as educational

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environments and professional projects, the formation of effective groups plays a crucial role in achieving desired outcomes [3]. Traditional group-formation procedures, such as random assignment or subjective selection by an authority person, may neglect critical team-building variables. These techniques can result in teams with a lack of variety in abilities, perspectives, and work styles, limiting their capacity to tackle complicated tasks and innovate successfully. The recent interest in applying data analysis techniques for enhancing group formation processes has emerged as a promising avenue to resolving these difficulties. However, existing research is mostly concerned with theoretical frameworks rather than practical methodologies to implement data driven approaches to group formation [4-6]. While clustering algorithms have been applied in a variety of fields, such as marketing and biology, limited research has focused on the use of the *K*-means clustering method for group assignment in collaborative situations. This gap emphasises the necessity for empirical research to create and validate practical methodologies for leveraging clustering algorithms in group formation [7]. Student group formation is an important instrument for improving the process of teaching and learning in the most effective way for students; it is an essential activity that enhances collaborative, peer-to peer learning. Optimizing group formation is vital for encouraging successful group work in higher education, which is critical for enhancing students' learning experiences and outcomes, yet study findings are still inconclusive [6].

There are three main attributes considered in the formation of group assignments: work preferences, analytical skills, and student achievement [8-10]. Work preferences refer to an individual's preferred way of working, including their preferred roles, collaboration style, task approach, and working environment. Analytic skills is an ability to collect, interpret, and evaluate information to solve problems, make decisions, and identify patterns. Whereas a student performance is a student's level of achievement in academic tasks, typically measured through grades, assessments, participation, and overall learning progress [10-13]. It reflects how well a student understands and applies knowledge in their studies.

This study aims to examine and develop a formation for creating effective task groups to achieve optimal results. Therefore, several aspects need to be examined before forming an optimal task group, namely identifying and testing the attributes/characteristics contributing to group formation. Secondly, this study will propose a combination of group members using the *K*-Means clustering method. Lastly, a comparison will be made between the results obtained using the *K*-Means method and the traditional method.

The probability of variation in student performance in traditional group assignments is high due to the previously mentioned factors. Therefore, this study offers an alternative to reduce such variation by forming groups that combine high-achieving and lower-achieving students within the same group. Group formation using *K*-means methodologies highlights the need for systematic and data-driven approaches that can enhance the process of team formation. Leveraging advanced analytical techniques. However, significant questions persist regarding the identification of relevant attributes for clustering, the optimization of clustering parameters, and the integration of clustering results into actionable group assignments [14,15]. Furthermore, the influence of inefficient group formation procedures extends beyond immediate team dynamics, influencing overall collaborative outcomes [16,17]. In light of these limitations, the purpose of this study is to determine the effectiveness of data-driven techniques, namely the use of the *K*-means clustering algorithm, in enhancing the group formation process. In order to improve collaborative outcomes and advance team-based work practices in a variety of professional and academic settings, this research intends to systematically examine the factors influencing group assignment and develop strategies to optimize clustering-based group formation.

2. Methodology

Group formation in educational contexts is crucial in fostering collaborative learning experiences and improving academic outcomes [18]. Traditional methods of group assignment frequently overlook crucial factors such as skills diversity, personality characteristics, and team member compatibility, resulting in suboptimal group compositions that may hinder overall performance [19]. Figure 1 illustrates the process undertaken in completing this study. Identifying attributes/characteristics is based on previous studies, where all factors that need to be considered in group task formation are taken into account. Next, a real data was collected on the identified attributes/characteristics. Two sets of real data are collected: group assignment data formed using the traditional method and data formed using the *K*-Means method.

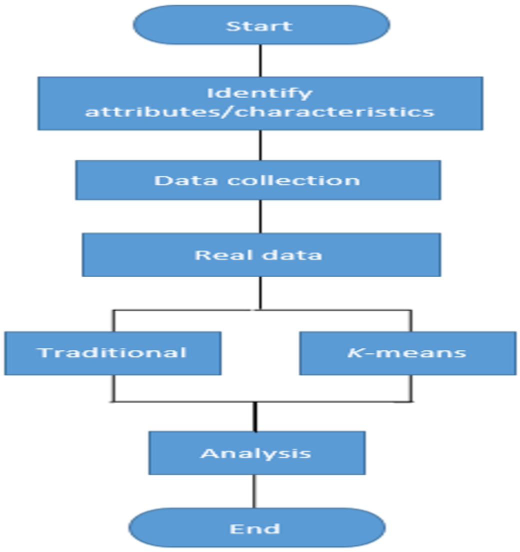

Fig. 1. Research process

2.1 Attribute Identification

The formation of group members in group assignments is based on three attributes that have been discussed previously. Table 1 shows the types of attributes as well as the data measurements used. These data were collected using a standardized procedure to ensure validity and relevance. Work preferences were evaluated through a self-reported scale in how students rated their preferences for certain roles or tasks within group assignments. Data on analytics skills were acquired from students' previous academic assessments, reflecting their ability to solve statistical and analytical problems. Academic performance data, specifically score in pre-group assignment, were used to assess the influence of clustering-based group formation on both individual and group outcomes. These variables were chosen based on their alignment with the study's objectives and the theoretical framework emphasizing the importance of aligning complementary attributes for effective group formation. By focusing on these characteristics, the study provides a reliable method for analysing and optimizing team dynamics using the *K*-means clustering technique.

Table 1
Measurement scale for attribute

Attribute	Measurement
Work preferences	Likert scale (1 – 10)
Analytics skills	Ratio (percentage)
Student performance	Ratio (score)

2.2 Data Collection

The study mainly relies on primary data collected from students enrolled in the Inferential Statistics course at Universiti Utara Malaysia (UUM). These data include several key variables required for group formation, including work preferences (measured on a quantitative scale indicating preferences on a scale from 1 to 10), analytics skills (quantitative data measured as score in percentage from assessments), and student performance (score) before and after group formation, which were selected based on the framework established by [6]. Figure 2 illustrates the data collection process for group formation. Before the formation of the groups, each student was given a questionnaire to identify the attributes possessed by each student. The results from this questionnaire will be used in the group formation using the *K*-Means approach

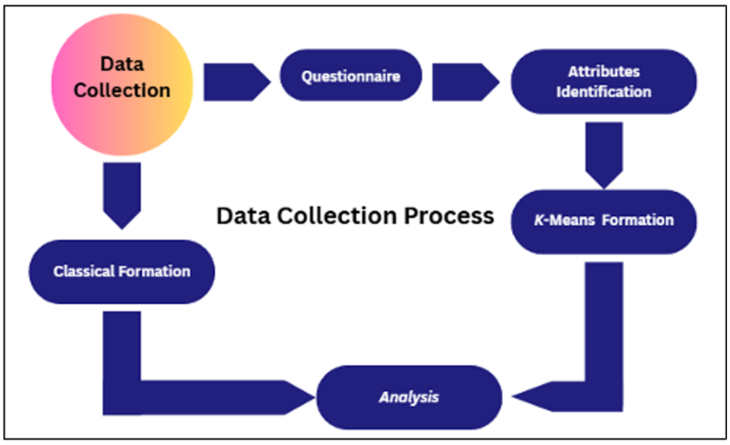

Fig. 2. Data collection process

2.3 Group Formation

In this section, the formation of group assignments is divided into two parts, namely traditional formation (control group) and also the group formed using the K-means method. As shown in Figure 2, initially, students will form groups traditionally, where they are free to choose their group members. Then, a task, which is contain the same questions is assigned to each group. The scores for each group are recorded to be compared with the scores of the group formed using the K-means method. The number of groups formed (G) depends on the number of students in the class (N), with the condition that each group must have only three to five members. We can simplify these number as in Eq. (1)

$$N=G_1+G_2+\cdots+G_m=n_1+n_2+\cdots+n_m=k_1+k_2+\cdots+k_m \quad (1)$$

Where N = total number of student in the class, G = number of group, n_i = number of members in group i (traditional method), k_j = number of members in group j (K-means method), and $3 \le n,k \le 5$

In the group formation phase using the K-means method, an analysis of the questionnaire is conducted to determine the number of students in each cluster based on all the attributes studied. The determination of the optimal number of clusters can be done using a Gap Statistics method. The Gap Statistics method compares the total within-cluster variation for different numbers of clusters with their expected values under null reference distributions. We can determine the optimal number of cluster using the formula in Eq. (2) and Eq. (3).

Gap (K)=1/N ∑_(n=1)^N▒log[W_k^* (n)-log(W_k)] (2)

Where logW_k^* (n) is the within-cluster dispersion for the nth reference dataset, and log(W_k) is the within-cluster dispersion for the original data.

Gap(K)≥Gap(K+1)- s_(K+1) (3)

3. Analysis and Results

This section discusses the analysis and results of the analysis conducted. It covers the formation of group assignments both traditionally and using the K-means approach. A comparison of the results between the two methods is also discussed further in this section.

3.1 Determining the Optimal Number of Cluster

Selecting the optimal number of clusters is a crucial step in the clustering process, as it ensures that the data is grouped in a meaningful way. Figure 3 shows the Gap Statistic graph plotted the gap value against the number of clusters (K). The gap statistic increases significantly at K= 4 and stabilizes after a steep increase, confirming that this number of clusters provided the optimal balance between within-cluster homogeneity and between-cluster separation. This represented the point where the clustering of the actual data was significantly better than that of random datasets.

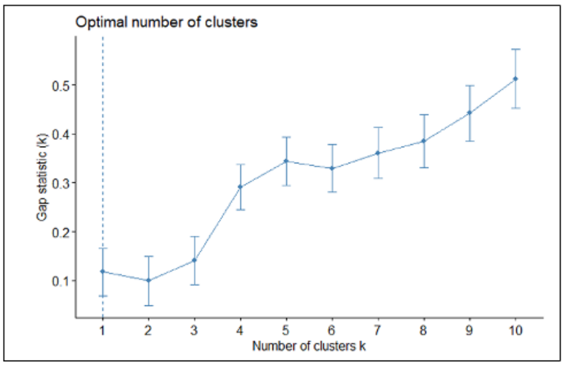

Fig. 3. Gap statistics graph

3.2 Analysing Factors Contributing to Group Formation Successes

The *K*-means clustering algorithm was applied with the number of clusters set to four, based on the results from the Gap Statistic Methods. Each cluster was analysed to identify its unique characteristics based on the standardized values of work preferences, analytics skills, and score. The sizes of the clusters varied, ranging from 8 to 18 members, and their means for each variable are summarized in Table 2.

Cluster 1 comprised students with the highest Analytics Skills and scores, coupled with modest work preferences scores. This cluster, referred to as "High Performers," included students who excelled academically and possessed good analytical skills, making them ideal for jobs that required significant cognitive and analytical participation.

Cluster 2 showed moderate levels for all variables. These students had a balanced profile, with average analytics skills, score, and slightly higher-than-average work preferences. These students, classified as "Moderate Performers," were most likely adaptive and capable of contributing in a variety of group settings.

Cluster 3 was characterized by the lowest values for all three variables, including significantly below-average work preferences, analytics skills, and score. This group, termed "Low Performers", likely comprised students who required additional support and guidance to perform effectively in group assignments.

Cluster 4 was distinctive in that it had moderate work preferences but below-average scores for analytics skills and score. The mismatch between preferences and actual abilities revealed that these students may overestimate their ability to accomplish tasks or prefer tasks that do not fit with their competences. This cluster was categorized as "Misaligned Preferences."

Table 2
Cluster means for each attribute

Cluster	Work Preference	Analytics Skill	Score	Cluster Size
1	0.07886227	1.6014197	1.5901216	10
2	0.56568970	0.2037432	0.2674259	14
3	-1.87890935	-0.5168055	-0.5133751	8
4	0.35127758	-0.8184532	-0.8632321	18

The clustering results were visualized using a 2D plot shown in figure 4, where the data points were projected onto two principal dimensions representing the majority of the variability in the dataset. Each cluster was represented by a different colour and was visibly distinct in the plot, reinforcing the conclusion that the clusters were well-separated. The visualization provided a clear picture of how students were grouped based on the three key variables.

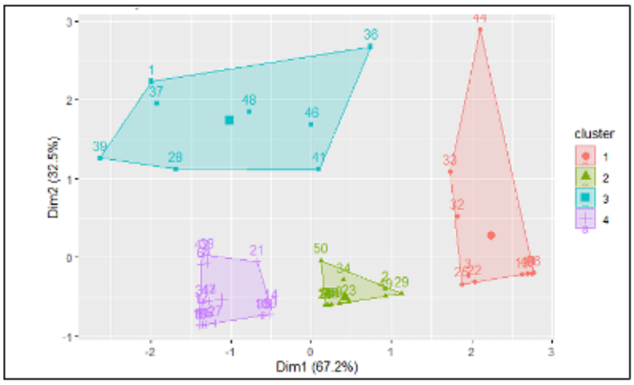

Fig. 4. Cluster plot

Based on Table 2 and Figure 4, to achieve the objective of forming 10 balanced and high-performing groups for group assignments, students were strategically distributed based on their respective clusters identified during the K-means clustering analysis. Each cluster has different characteristics: Cluster 1 (High Performers), Cluster 2 (Moderate Performers), Cluster 3 (Low Performers), and Cluster 4 (Misaligned Preferences). The objective was to create a diverse mix of performance levels and preferences in each group to foster collaboration, effective teamwork, and overall success. The given cluster sizes were Cluster 1 (10 students), Cluster 2 (14 students), Cluster 3 (8 students), and Cluster 4 (18 students). The allocation was carefully planned to ensure proportional representation from each cluster while maintaining balance. Specifically, each group includes one student from Cluster 1 (High Performers), as they provide strong academic support and leadership to the teams. Students from Cluster 2 (Moderate Performers) were distributed with one to two students per group, providing a balanced skill level to complement the High Performers. Cluster 3 (Low Performers) was allocated with zero or one student per group to prevent overburdening the teams and to provide opportunities for these students to learn and grow in a supportive environment. Finally, Cluster 4 (Misaligned Preferences) included one to three students per group, introducing diversity in work preferences and roles, which can enhance team creativity and adaptability.

Table 3 below shows the suggested group allocation. This strategic grouping results in balanced teams that incorporate students with various strengths and weaknesses, aiming to foster high-performing groups capable of tackling complex assignments effectively. The diversity in clusters within each group ensures that teams benefit from complementary skills, providing opportunities for peer learning and collaborative problem-solving. Furthermore, this structure is designed to encourage students with misaligned preferences to adapt and contribute positively within the team environment. The allocation of students into these 10 groups reflects a thoughtful balance of performance levels and work preferences, ensuring fairness and inclusivity while addressing the overall objective of creating effective and productive teams.

Table 3
Proposed group allocation

Group	High Performance	Moderate Performance	Low Performance	Misaligned Preference	Total
1	1	1	1	2	5
2	1	2	1	1	5
3	1	1	0	3	5
4	1	2	1	1	5
5	1	1	1	2	5
6	1	2	1	1	5
7	1	1	0	3	5
8	1	2	1	1	5
9	1	1	1	2	5
10	1	1	1	2	5
Total	10	14	8	18	50

3.3 Comparing Group Performance

This section addresses the third objective, which aims to compare the performance of groups formed using *K*-means clustering with those formed without clustering. The study focuses on changes in students' scores before and after group formation, to investigate whether clustering contributes to improved outcomes. To accomplish this, statistical approaches such as summary statistics, paired t-tests, and subgroup analyses were used.

The students' score before and after the group formation process were compared to 0.495 determine the influence of clustering-based group formation. The results are summarized in Table 4. From the table, it shows a significant improvement: the average score (measured according to CGPA) climbed from 2.59 to 3.46, resulting in an average improvement of 0.873 points. This represents a substantial academic gain across the student groups. Furthermore, the variability in score, assessed by standard deviation, reduced slightly from 0.574 (before) to 0.503 (after), indicating that students performed more consistently after group formation. The improvement observed underscores the potential of clustering-based grouping to enhance group performance by creating teams with complementary attributes and skills. This method tends to foster collaboration and learning, ultimately leading to better academic outcomes for the majority of participants.

Table 4
Mean score and standard deviation before and after clustering

Mean	Standard deviation
2.59	0.57
3.46	0.503

A paired t-test was conducted to validate the observed score improvement. The results indicate a highly significant difference between the mean score before and after group formation ($p = 2.2 \times 10{-}16, \propto = 0.05, p < 0.05$). The 95% confidence interval for the mean difference ($-1.013, -0.732$) excludes zero, confirming the effectiveness of clustering in driving this improvement. The test results show that clustering-based group formation improves student academic performance significantly. The mean improvement of 0.873 points is not only statistically significant, but also practically meaningful, demonstrating the method's potential to increase group productivity.

To better understand the dynamics of score improvement, students were divided into two subgroups and it have summarized in Table 5. Improved Group: Students whose score improved by more than 0.5 points. Moderate Group: Students whose score improved by 0.5 points or less. The Improved Group, which included 37 students, exhibited a mean score improvement of 1.08 points (from 2.40 to 3.48). This group predominantly included students 21 with lower initial score, who benefited the most from clustering-based group formation. The combination of complementary skills and work preferences within these groups most likely produced a supportive atmosphere in which these students could thrive academically. In contrast, the Moderate Group, consisting of 13 students, showed a smaller mean score increase of 0.28 points (from 3.13 to 3.41). Students with higher initial score had less space for improvement, implying that clustering benefited them less significantly.

However, their performance still improved, indicating that even academically excellent students can benefit from well-formed groups. The subgroup analysis highlights the ability of clustering to optimize group dynamics, particularly for students with different academic baselines. Clustering individuals based on their strengths and weaknesses fosters a balance of skills and learning opportunities will enhance group performance.

Table 5
Analysis of score improvements across subgroups

Cluster	Average score			Count
	Before	After	Difference	
Improved	2.40	3.48	1.08	37
Moderate	3.13	3.41	0.28	13

4. Limitation of Study and Recommendation

This study is a pilot study conducted on 50 students enrolled in the Inferential Statistics course. The sample size is relatively small. If the sample size taken is small, several implications on the research findings may arise:

i. Reduced reliability of finding. Small sample size can result in less stable findings and may not accurately represent the actual population. This increases the likelihood that the results are due to chance rather than true patterns within the population.
ii. High sampling error. Sampling error refers to the difference between sample statistics and the actual population parameters. With a small sample, this error tends to be larger, making parameter estimates less accurate.
iii. Decrease confidence in statistical inference. Hypothesis testing and estimates such as confidence intervals become less robust with a small sample. The confidence intervals tend to be wider, indicating greater uncertainty in the estimates.
iv. Low statistical power. A small sample size results in low statistical power to detect a true effect (if one exists). This means the study may fail to identify real differences (increased risk of Type II error).
v. Risk of inaccurate conclusions. Since data from a small sample may not reflect the variation within the actual population, there is a higher risk of drawing incorrect conclusions, especially if the sample is not randomly selected or does not adequately represent the population.

To address the issue of a small sample size, several measures can be considered. One of the main steps is to increase the sample size in future studies so that the findings are more representative of the actual population and have greater statistical power. In addition, employing more effective sampling techniques, such as stratified sampling or cluster sampling, can help ensure that each subgroup within the population is adequately represented, even with a limited number of respondents. This pilot study can also serve as a foundation for planning a larger-scale study in the future. From an analytical perspective, applying statistical methods suitable for small samples, such as non-parametric tests, can help ensure the results remain valid and reliable. Furthermore, selecting samples randomly is important to reduce bias and enhance the representativeness of the sample. If related studies exist, a meta-analysis approach can be used to combine data and produce more comprehensive and robust findings.

In addition, this study only focuses on factors such as work preference, analytical skills, and student scores. Internal factors within the students themselves, such as individual characteristics, learning styles, or personal issues, should also be taken into consideration.

i. Individual characteristics. Individual traits such as communication skills, personality, learning styles, and motivation significantly impact how students participate in group tasks. Effective communication allows students to express their ideas clearly and understand others, facilitating collaboration. Personality also plays a key role—dominant students may naturally assume leadership roles, while introverted students may contribute less actively. Additionally, students' learning styles (visual, kinesthetic, or auditory) influence how they approach tasks, and those with higher levels of commitment and motivation are often more proactive in contributing to the group effort.
ii. Group structure and dynamics. The internal structure and dynamics of the group determine how tasks are divided and how decisions are made. Clearly defined roles and responsibilities help prevent misunderstandings and ensure that all group members contribute. Effective leadership within the group is essential for guiding the team toward its common goals. The decision-making

process, whether based on majority votes, consensus, or the guidance of a specific leader, also affects group cohesion and efficiency.

iii. Personal issues. External factors, such as the guidance and support provided by the instructor, play a significant role in the success of group assignments. Clear instructions and ongoing supervision from the lecturer can help keep the group on track. Access to resources, such as reading materials, research databases, and time for collaboration, also greatly affects the quality of the final output. Additionally, the use of collaborative platforms, such as Google Docs, Microsoft Teams, or Moodle, can facilitate communication and the sharing of information, making collaboration more efficient.

In conclusion, the formation and success of group assignments settings depend on a combination of internal and external factors such as work preference, analytical skills, student scores individual characteristics, group dynamics, and personal issues. By understanding and addressing these factors, educators and students can work together to create more effective and productive group experiences.

5. Conclusions

The results of this study emphasize the critical importance of K-means clustering to improved group productivity. One of the key benefits identified is enhanced collaboration, where the alignment of complementary skills and preferences within groups fosters a cooperative learning environment. By carefully matching each student based on their skills, clustering fosters synergy, allowing team members to learn from one another and contribute more effectively to group assignment. This structured method stands in sharp contrast with random or arbitrary group formation methods, which frequently neglect the potential advantages of balancing group members' strengths and limitations. Furthermore, students who started with lower initial score improved their academic performance are the evidenced by the significant increase in the average score. This demonstrates that clustering-based group formation can uplift underperforming students by placing them in supportive teams that are matched to their specific learning needs. Even students with higher score, who exhibited smaller improvements, still benefited from the optimized team dynamics, reinforcing the universal applicability of clustering across different academic levels. Other than that, performance variability is reduced, as indicated by the decreased standard deviation in score after group formation. This shows that clustering not only enhances individual performance, but also creates more consistent results within groups. Clustering reduces disparities by balancing the distribution of skills and attributes, ensuring that all team members are equipped to provide significant contributions to the group's performance. In conclusion, these findings indicate that clustering-based group formation improves productivity by fostering teamwork, addressing performance disparities, and forming balanced and successful groups. The systematic nature of this method makes it a valuable tool for lecturers aiming to maximize their students' potential, with significant advantages over traditional group formation practices.

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