

# Student Engagement Profiles in a Collaborative-Competitive Learning Environment: Evidence from an Industrial Statistics Course

Yunita Nugrahaini Safrudin<sup>1\*</sup>, Ni Putu Ayu Laksmi<sup>2</sup>, Hilman Dwi Anggana<sup>3</sup>, Wiyono<sup>4</sup>

<sup>1,2,3,4</sup> Industrial Engineering Study Program, School of Industrial Engineering, Telkom University, Main Campus (Bandung Campus), Bandung, Indonesia

<sup>1</sup>Email: yunitanugrahainis@telkomuniversity.ac.id

*Proceedings of the Kalijaga International Conference on Education 2026*

**Abstract.** This study investigates student engagement profiles in a collaborative-competitive learning environment within an Industrial Statistics course at a university in Indonesia. The research employed a quantitative survey design involving 200 undergraduate students who experienced a pedagogical model combining within-group collaboration and inter-group competition. Cluster analysis using K-means algorithm identified three distinct engagement profiles based on four constructs: collaboration quality, attitude toward group work, learning outcome, and competitive orientation. Reliability analysis showed good internal consistency across all constructs (Cronbach's  $\alpha = 0.802\text{--}0.850$ ). The optimal cluster solution was determined using the elbow method and silhouette coefficients. The three profiles represent students with high engagement, moderate engagement, and disengagement respectively. As a supplementary analysis, case study scores from 89 students were examined to explore the relationship between engagement profiles and academic performance. Pearson correlation analysis revealed weak positive correlations between learning outcome and case study scores ( $r = 0.228$ ). The findings suggest that while the collaborative-competitive model effectively engages the majority of students, approximately one-third of students has low engagement and require differentiated pedagogical support. This study contributes to the growing body of research on student engagement in collaborative learning environments and provides practical implications for designing inclusive instructional strategies.

**Keywords:** cluster analysis; collaborative-competitive learning; engagement profiles; higher education; industrial statistics; student engagement

**Abbreviations:** ATGW (Attitude toward Group Work); CO (Competitive Orientation); CQ (Collaboration Quality); LO (Learning Outcome)

## INTRODUCTION

Quantitative courses are often perceived by students as challenging, with statistics being among the most demanding. In the field of industrial engineering, students are required to master statistical concepts to support data-driven decision making. Industrial Statistics demands an understanding of abstract concepts, numerical analytical skills, and integrated problem-solving abilities. However, this level of complexity is frequently difficult to achieve through traditional lecture-centred instructional approaches, in which students tend to function as passive recipients of information. Such patterns not only risk diminishing student engagement but also increase cognitive overload, thereby hindering the optimal development of conceptual understanding [1]. In the context of quantitative modelling, these conditions may impede students' ability to solve real-world industrial problems.

One approach recommended to address low levels of student engagement in learning activities is collaborative learning. Through group work, students have opportunities for social interaction, peer explanation, and active participation in meaning-making processes. This approach is consistent with Social Constructivism and Social Interdependence Theory, which emphasize the importance of positive interdependence among group members in achieving shared goals [2]. Although collaboration has been shown to enhance participation, its implementation does not always yield uniform responses. Some students benefit from group discussions, whereas others may feel uncomfortable, dominated by certain members, or insufficiently engaged. Phenomena such as social loafing and individual dominance often hinder the realization of inclusive learning objectives [3].

Conversely, the incorporation of competition in learning is often viewed as a driver of motivation. Competitive elements can stimulate greater effort and focus through achievement-oriented incentives [4].

However, competition may also increase student anxiety and reduce psychological safety. The concept of collaborative–competitive learning (coopetition) seeks to reconcile this tension by combining cooperation within groups with competition between groups. Within this instructional design, students are encouraged to support one another in striving for superior performance relative to other groups. This approach has been shown to enhance engagement while simultaneously strengthening intrinsic and extrinsic motivation [5], [6].

Nevertheless, the systematic investigation of coopetition in quantitative courses such as Industrial Statistics remains limited. Most prior studies have examined the effectiveness of collaborative learning or competition in isolation, with a primary focus on aggregated improvements in average learning outcomes [7]. Few studies have explicitly examined this combined approach using data-driven methods to capture heterogeneity in student responses. Common analytical approaches continue to rely predominantly on regression or Structural Equation Modeling (SEM), which assume student populations to be homogeneous [8]. In reality, student engagement profiles are highly heterogeneous.

The same instructional model may therefore yield differential effects depending on students' psychographic characteristics. The application of unsupervised learning methods such as cluster analysis offers a novel means of objectively profiling patterns of student engagement based on empirical data, an approach that remains underutilized in higher education, particularly within engineering programs [9]. Insights into such segmentation are crucial for enabling instructional differentiation and supporting adaptive teaching practices. Building on this research gap, the present study aims to identify profiles of student engagement in collaborative–competitive learning within an Industrial Statistics course using a cluster analysis approach.

## METHODS

### Research Design and Context

This study employed a quantitative, cross-sectional survey design to identify student engagement profiles in a collaborative-competitive learning environment. The research was conducted in an Industrial Statistics course during the 2025/2026 academic semester at a university in Indonesia. The course implemented a collaborative-competitive learning model that systematically combined within-group collaboration and inter-group competition. At the beginning of the semester, students were organized into small groups of 4–5 members and remained in these groups throughout the course to facilitate the development of trust, communication, and collaborative problem-solving skills. Within-group collaboration involved completing statistical case studies and problem-solving tasks or quizzes. Inter-group competition was structured through a series of problem-solving challenges named StatWars, in which groups competed to solve increasingly complex statistical problems within limited time frames.

### Participants

A total of 200 undergraduate students enrolled in the Industrial Statistics course participated in this study through convenience sampling. The sample comprised 167 male students (83.5%) and 33 female students (16.5%), reflecting the typical gender distribution in engineering programs at the institution. All participants were in their second year of study and had completed prerequisite statistics courses. For the supplementary analysis examining academic performance, case study scores were available for 89 students.

### Instrumentation

The questionnaire was developed through adaptation from established framework in the literature. The instrument comprised 13 items measuring four constructs, namely Collaboration Quality (3 items), Attitude toward Group Work (3 items), Learning Outcome (3 items), and Competitive Orientation (4 items). CQ and ATGW were informed by the UWE Entry Level Interprofessional Questionnaire (ELIQ), which measure communication, teamwork, and attitudes toward cooperation [10]. LO was grounded in Johnson and Johnson's framework of cooperative learning outcomes, which links structured group work to cognitive gains [2]. CO was adapted from the Cooperative and Competitive Orientation Scale, which captures motivational and affective aspects of competition [11]. All items were measured on a 6-point Likert scale ranging from 1 (strongly disagree) to 6 (strongly agree).

Reliability analysis using Cronbach's alpha demonstrated good internal consistency for all constructs: Collaboration Quality ( $\alpha = 0.802$ ), Attitude toward Group Work ( $\alpha = 0.819$ ), Learning Outcome ( $\alpha = 0.824$ ), and Competitive Orientation ( $\alpha = 0.850$ ). These values exceed the recommended threshold of 0.70 for exploratory research [12].

Case study scores were obtained from course instructors as indicators of academic performance. These scores were derived from individual case study assessments completed during the semester.

## Data Collection Procedures

Data were collected during the final week of the semester to ensure students had sufficient experience with the collaborative-competitive learning model. Students were informed about the research purpose, and the questionnaire was administered in LMS. Case study scores were obtained from course instructors with student consent, using a standardized rubric that had been agreed upon with students at the beginning of the semester. These scores reflected students' individual performance on case-based assessments completed throughout the course.

## Data Analysis

Composite scores for each construct were calculated by averaging item responses for each respondent [13]. Preliminary data screening included examination of missing values, outliers using z-scores (threshold  $|z| > 3.29$ ) [14], and multicollinearity using Variance Inflation Factor (VIF). Cluster analysis using the K-means algorithm was performed on standardized composite scores (z-scores). The optimal number of clusters was determined using: (1) the elbow method examining within-cluster sum of squares (inertia); and (2) silhouette coefficients [15]. Cluster profiling was conducted by examining final cluster centres on the original 1-6 scale.

## RESULTS AND DISCUSSION

### Preliminary Data Screening

Preliminary screening revealed no missing values in the engagement questionnaire data. Outlier analysis using z-scores with threshold  $|z| > 3.29$  identified no univariate outliers. Examination of multicollinearity using Variance Inflation Factor (VIF) showed all values below 5.0 (ranging from 1.89 to 2.45), indicating no problematic multicollinearity [12]. The correlation matrix revealed moderate to strong correlations among engagement constructs ( $r = 0.60$ – $0.75$ ), suggesting these constructs represent interrelated yet distinct dimensions of student engagement.

### Reliability and Descriptive Statistics

Reliability analysis confirmed good internal consistency across all constructs (Table 1). Descriptive statistics showed that mean scores for all constructs were above the mid-point of the scale (3.5), indicating generally positive perceptions among students toward the collaborative-competitive learning experience.

**Table 1. Descriptive Statistics and Reliability of Engagement Constructs (N=200)**

| Construct                  | Mean | SD   | Cronbach's $\alpha$ |
|----------------------------|------|------|---------------------|
| Collaboration Quality      | 4.92 | 0.98 | 0.802               |
| Attitude toward Group Work | 4.76 | 1.12 | 0.819               |
| Learning Outcome           | 4.85 | 1.05 | 0.824               |
| Competitive Orientation    | 4.85 | 1.08 | 0.850               |

### Cluster Analysis Results

The elbow method revealed a bend at  $k=2$  to  $k=3$ , with the silhouette coefficient indicating  $k=3$  as the optimal solution (silhouette = 0.407). The three-cluster solution was selected for its theoretical interpretability and acceptable cluster separation. Table 2 presents the final cluster centres and distribution of students across the three profiles.

**Table 2. Cluster Centers and Distribution (N=200)**

| Cluster | n (%)       | Collaboration Quality | Attitude toward Group Work | Learning Outcome | Competitive Orientation |
|---------|-------------|-----------------------|----------------------------|------------------|-------------------------|
| 0       | 112 (56.0%) | 5.52                  | 5.61                       | 5.68             | 5.59                    |
| 1       | 74 (37.0%)  | 4.71                  | 4.50                       | 4.60             | 4.52                    |
| 2       | 14 (7.0%)   | 3.83                  | 3.14                       | 2.78             | 3.66                    |

Figure 1 presents the clustering results of students projected onto a two-dimensional space using Principal Component Analysis (PCA). Each point represents an individual student, while different colors indicate the cluster assignments obtained from the clustering process. The visualization shows three distinct groups with different spatial distributions. Cluster 0 (red) is mainly concentrated in the positive region of the first principal component, whereas Cluster 1 (blue) occupies the central region with a relatively wider dispersion. Cluster 2 (green) is positioned considerably farther from the other two groups, particularly along the first principal component. The relatively clear separation among the clusters suggests that the students exhibit different patterns across the variables used in the clustering analysis.

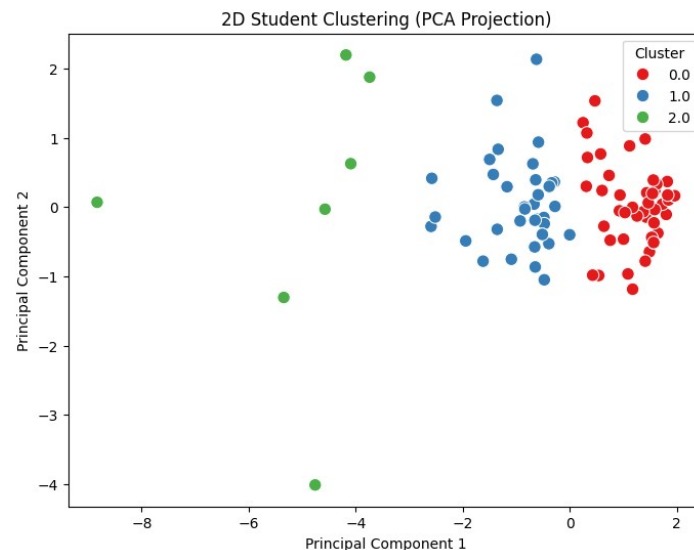


Figure 1. Clustering Result

The following sections explain each cluster:

#### Cluster 0 (red): Highly Engaged Learners (56.0%)

Students in this cluster recorded consistently high scores across the measured constructs, ranging from 5.52 to 5.68. They perceived group collaboration positively, reported strong learning gains, and showed high motivation toward competition. The consistency of these scores suggests that this group responded particularly well to the collaborative-competitive learning model, with both the collaborative and competitive elements contributing positively to their learning experience.

#### Cluster 1 (blue): Moderately Engaged Learners (37.0%)

Students assigned to this cluster obtained moderate scores across the constructs, ranging from 4.50 to 4.71. Overall, their responses remained positive, but the scores were lower than those observed in Cluster 0. This pattern suggests that these students were able to participate in the collaborative-competitive learning activities, although the perceived benefits and motivational effects were not as strong as those reported by the highly engaged group.

#### Cluster 2 (green): Low Engagement Learners (7.0%)

This cluster represents a small proportion of students whose scores were considerably lower, ranging from 2.78 to 3.83. The lowest scores were observed for learning outcomes (2.78) and group collaboration (3.14), indicating fewer positive experiences with both the collaborative process and the resulting learning gains. Although this group accounts for only 7.0% of the sample, its profile suggests that the collaborative-competitive learning model did not provide the same level of engagement and perceived benefit for these students as it did for the other groups.

#### Relationship Between Engagement and Academic Performance

As a supplementary analysis, case study scores were examined for the subset of 89 students. One-way ANOVA revealed no statistically significant difference in case study scores across engagement clusters ( $p = 0.662$ ). Pearson correlation analysis revealed weak positive correlations between engagement constructs and case study scores (Table 3). Learning Outcome demonstrated the highest correlation with case study scores ( $r = 0.228$ ). Collaboration Quality showed a very weak positive correlation ( $r = 0.126$ ), while Attitude toward Group Work ( $r = 0.002$ ) and Competitive Orientation ( $r = -0.021$ ) showed negligible correlations.

Table 3. Correlations with Case Study Scores (N=89)

| Construct                  | r      | p-value | Interpretation |
|----------------------------|--------|---------|----------------|
| Learning Outcome           | 0.228  | 0.131   | Weak positive  |
| Collaboration Quality      | 0.126  | 0.432   | Very weak      |
| Attitude toward Group Work | 0.002  | 0.972   | Negligible     |
| Competitive Orientation    | -0.021 | 0.834   | Negligible     |

## Discussion

### Interpretation of Engagement Profiles

The three engagement profiles identified in this study reveal that students do not respond uniformly to the collaborative-competitive learning model. The Highly Engaged Learners (56%) represent the majority for whom the pedagogical approach was successful. Similar to findings from [16], students with more positive learning orientations tended to engage more deeply with collaborative activities. The high scores on Competitive Orientation in this group suggest that competition, when structured as inter-group rather than intra-group, can strengthen within-group collaboration [17].

The Moderate Engagement Learners (37%) represent a significant segment of students who participated adequately but without strong enthusiasm. Their moderate scores across all constructs suggest potential for improvement through targeted pedagogical interventions. This group may benefit from additional scaffolding or opportunities to develop collaborative skills [18].

The Disengaged Learners (7%) represent a small but concerning minority for whom the model failed. Their low attitude toward group work is particularly critical, suggesting prior negative experiences or strong individual learning preferences. This finding echoes concerns raised by researchers about the potential for cooperative learning models to alienate students who prefer individualistic learning approaches [19], [20]. For this group, alternative pedagogical strategies or differentiated support may be necessary.

### Engagement and Academic Performance

The non-significant difference in case study scores across clusters and weak correlations between engagement constructs and scores are consistent with findings from Han et al. [16], who reported that SNA centrality measures explained only small amounts of variance in academic achievement when assessments were predominantly individual. Similar to their study, most assessment tasks in this course were individual in nature, which may have attenuated the relationship between collaborative engagement and performance.

The positive correlation between Learning Outcome and case study scores ( $r = 0.228$ ), although not significant, suggests that students who perceived greater learning gains from the model tended to perform slightly better. This finding aligns with self-efficacy theory [21], which posits that students' beliefs about their learning capabilities can influence their academic achievement.

### Practical Implications

The identification of distinct engagement profiles offers practical guidance for instructors implementing collaborative-competitive learning models. For Highly Engaged Learners, providing greater autonomy, increasing task complexity, and leveraging them as peer tutors may sustain their engagement. For Moderate Engagement Learners [18], explicit collaborative skills training and structured role assignments may help deepen their engagement. For Disengaged Learners, early diagnosis, intentional group formation with skilled peers, and individual assessment alternatives may prevent complete disengagement. The non-significant engagement-performance relationship suggests that engagement profiles provide valuable insights into students' learning experiences beyond what grades alone can capture. Instructors should recognize engagement as an important educational outcome in its own right [22] and not solely as a means to improve grades.

These recommendations can be embedded into the course structure. In the first week, a brief questionnaire helps identify students with negative attitudes toward group work [23]. In the second week, groups can be formed intentionally, placing disengaged students with highly engaged peers rather than leaving composition to chance [24]. A short workshop on collaborative skills can be conducted early, ideally before the first major group assignment [12].

Throughout the semester, instructors can assign rotating roles within each group to ensure every member contributes meaningfully [14]. After each session, groups can spend a few minutes reflecting on their teamwork to help students gradually recognize the value of collaboration [25]. At mid-semester, a short check-in survey can help identify struggling groups, allowing instructors to intervene early. For students who remain unable to engage effectively in group work, individual assessment alternatives can prevent disengagement from turning into academic failure [26]. This integrated approach ensures that the collaborative-competitive model is adapted to the diverse needs revealed by the engagement profiles.

### Limitation and Future Research

This study has several limitations that should be considered when interpreting the findings. First, the sample was drawn from a single course at one university, which may limit the generalizability of the results to other disciplinary or institutional contexts. Second, the cross-sectional design captures engagement at

one point in time, so the data do not allow for conclusions about how profiles might change over a semester. Third, the reliance on self-reported questionnaire data, while common in engagement research, may not fully capture actual student behaviours. Fourth, the supplementary analysis on academic performance was based on a smaller subsample (N=89), which reduced statistical power to detect small effects. Finally, the assessment tasks were predominantly individual in nature, which may have weakened the link between collaborative engagement and performance, consistent with previous observations by Han et al. [16].

Despite these limitations, the study offers meaningful insights into how students respond differently to collaborative-competitive learning models. Future research could strengthen these findings by employing larger and more diverse samples, using longitudinal designs to track engagement over time, incorporating observational or trace data alongside self-reports, and including collaborative assessments to better capture the relationship between engagement and academic outcomes. Mixed-methods approaches, such as combining surveys with interviews, would also help clarify the reasons behind students' engagement patterns and inform the design of targeted interventions.

## CONCLUSION

This study identified three distinct engagement profiles among students in a collaborative-competitive learning environment: Highly Engaged (56%), Moderate Engagement (37%), and Low-Engagement Learners (7%). The profiles differed significantly across collaboration quality, attitude toward group work, learning outcome, and competitive orientation. These findings demonstrate that students do not respond uniformly to the pedagogical model, with approximately 7% of students experiencing disengagement that may require differentiated support.

The supplementary analysis revealed no significant relationship between engagement profiles and case study performance, suggesting that engagement and academic achievement may be distinct constructs that are not directly linked in individual assessment contexts. This finding highlights the importance of assessing engagement as a valuable educational outcome, rather than solely as a predictor of grades.

Practical recommendations for instructors include early identification of at-risk students, intentional group formation to model desirable collaborative behaviours, explicit skills training for effective collaboration, and provision of individual assessment alternatives for students who cannot function in group settings. Future research should investigate engagement-performance relationships using collaborative assessments and employ longitudinal designs to track engagement changes over time.

## ACKNOWLEDGMENTS

The authors thank the students and instructors who participated in this study and PPM Telkom University that support financial of the research.

## REFERENCES

- [1] F. Paas and J. J. G. van Merriënboer, "Cognitive-Load Theory: Methods to Manage Working Memory Load in the Learning of Complex Tasks," *Curr. Dir. Psychol. Sci.*, vol. 29, no. 4, pp. 394–398, Aug. 2020, doi: 10.1177/0963721420922183.
- [2] D. W. Johnson and R. T. Johnson, "Cooperative Learning: The Foundation for Active Learning," in *Active Learning - Beyond the Future*, IntechOpen, 2019. doi: 10.5772/intechopen.81086.
- [3] K. Scager, J. Boonstra, T. Peeters, J. Vulperhorst, and F. Wiegant, "Collaborative Learning in Higher Education: Evoking Positive Interdependence," *CBE—Life Sciences Education*, vol. 15, no. 4, p. ar69, Dec. 2016, doi: 10.1187/cbe.16-07-0219.
- [4] J. C. Burguillo, "Using game theory and Competition-based Learning to stimulate student motivation and performance," *Comput. Educ.*, vol. 55, no. 2, pp. 566–575, Sep. 2010, doi: 10.1016/j.compedu.2010.02.018.
- [5] S. A. Aini and D. S. Ciptaningrum, "Exploring Students' Engagement in Blended Learning," *Britain International of Linguistics, Arts and Education*, vol. 6, no. 2, pp. 47–81, 2024.
- [6] D.-C. Wang and Y.-M. Huang, "Exploring the influence of competition and collaboration on learning performance in digital game-based learning," *Educational technology research and development*, vol. 71, no. 4, pp. 1547–1565, Aug. 2023, doi: 10.1007/s11423-023-10247-8.
- [7] S. Arnab, R. Bhakta, S. K. Merry, M. Smith, K. Star, and M. J. Duncan, "Competition and collaboration using a social and gamified online learning platform," in *Proceedings of the European Conference on Games-based Learning*, L. Boyle and T. M. Connolly, Eds., Paisley: Academic Conferences and Publishing International Limited, Oct. 2016, pp. 19–26.
- [8] N. M. Nazeef, A. Khan, and J. Ali, "Impact of Collaborative Learning on Student's Academic Performance in Teacher's Education Program," *Journal of Asian Development Studies*, vol. 13, no. 1, pp. 1054–1068, Mar. 2024, doi: 10.62345/jads.2024.13.1.87.

- [9] T. E. Virtanen, M.-K. Lerkkanen, A.-M. Poikkeus, and M. Kuorelahti, "Student Engagement and School Burnout in Finnish Lower-Secondary Schools: Latent Profile Analysis," *Scandinavian Journal of Educational Research*, vol. 62, no. 4, pp. 519–537, Jul. 2018, doi: 10.1080/00313831.2016.1258669.
- [10] K. C. Pollard, M. E. Miers, and M. Gilchrist, "Collaborative learning for collaborative working? Initial findings from a longitudinal study of health and social care students," *Health Soc. Care Community*, vol. 12, no. 4, pp. 346–358, Jul. 2004, doi: 10.1111/j.1365-2524.2004.00504.x.
- [11] X.-P. Chen, X. Xie, and S. Chang, "Cooperative and Competitive Orientation among Chinese People: Scale Development and Validation," *Management and Organization Review*, vol. 7, no. 2, pp. 353–379, Jul. 2011, doi: 10.1111/j.1740-8784.2011.00215.x.
- [12] H. Kara Erol, "Time for universities to think outside the box: University students' experiences of social skills development workshops," *Active Learning in Higher Education*, vol. 26, no. 1, pp. 139–156, Mar. 2025, doi: 10.1177/14697874231217054.
- [13] J. F. , B. W. C. , B. B. J. , A. R. E. Hair, *Multivariate Data Analysis*, 8th ed. Andover: Cengage Learning, 2019.
- [14] R. Elmoazen, M. Saqr, L. Hirsto, and M. Tedre, "Capturing temporal pathways of collaborative roles: A multilayered analytical approach using community of inquiry," *Int. J. Comput. Support. Collab. Learn.*, vol. 20, no. 1, pp. 41–77, Mar. 2025, doi: 10.1007/s11412-024-09431-6.
- [15] L. Kaufman and P. J. Rousseeuw, *Finding Groups in Data*. Wiley, 1990. doi: 10.1002/9780470316801.
- [16] F. Han, R. A. Ellis, and E. Guan, "Patterns of students' collaborations by variations in their learning orientations in blended course designs: How is it associated with academic achievement?," *J. Comput. Assist. Learn.*, vol. 39, no. 1, pp. 286–299, Feb. 2023, doi: 10.1111/jcal.12747.
- [17] R. E. Slavin, "Research on Cooperative Learning and Achievement: What We Know, What We Need to Know," *Contemp. Educ. Psychol.*, vol. 21, no. 1, pp. 43–69, Jan. 1996, doi: 10.1006/ceps.1996.0004.
- [18] M. Castillo, Y. Heredia, and K. Gallardo, "Collaborative Work Competency in Online Postgraduate Students and Its Prevalence on Academic Achievement," *Turkish Online Journal of Distance Education*, pp. 168–168, Jul. 2017, doi: 10.17718/tojde.328949.
- [19] P. Van den Bossche, W. H. Gijssels, M. Segers, and P. A. Kirschner, "Social and Cognitive Factors Driving Teamwork in Collaborative Learning Environments," *Small Group Res.*, vol. 37, no. 5, pp. 490–521, Oct. 2006, doi: 10.1177/1046496406292938.
- [20] W. M. Davies, "Groupwork as a form of assessment: common problems and recommended solutions," *High. Educ. (Dordr.)*, vol. 58, no. 4, pp. 563–584, Oct. 2009, doi: 10.1007/s10734-009-9216-y.
- [21] T. Honicke and J. Broadbent, "The influence of academic self-efficacy on academic performance: A systematic review," *Educ. Res. Rev.*, vol. 17, pp. 63–84, Feb. 2016, doi: 10.1016/j.edurev.2015.11.002.
- [22] J. A. Fredricks, P. C. Blumenfeld, and A. H. Paris, "School Engagement: Potential of the Concept, State of the Evidence," *Rev. Educ. Res.*, vol. 74, no. 1, pp. 59–109, Mar. 2004, doi: 10.3102/00346543074001059.
- [23] S. Kim and M. Kim, "Exploring the Causes and Solutions of Free-Riding in Team Collaboration Learning: Expert Solutions Based on Systematizing Prior Research," *The Korean Society of Culture and Convergence*, vol. 45, no. 7, pp. 179–197, Jul. 2023, doi: 10.33645/cnc.2023.07.45.07.179.
- [24] B. Scheidler, K. Layne, M. Gillard, and B. M. Doucet, "Intentional Grouping: Impacts on Cognitive and Social Presence in a Hybrid Classroom," *Journal of Occupational Therapy Education*, vol. 9, no. 2, Jan. 2025, doi: 10.26681/jote.2025.090210.
- [25] A. Pfennig and J. Siegeris, "REFLECTIONS FROM A STUDENT PERSPECTIVE - RESPONSE TO ACTION," Nov. 2024, pp. 1260–1269. doi: 10.21125/iceri.2024.0389.
- [26] X. Li, W. Hu, Y. Li, and Y. Zheng, "Individuals in a group: exploring engagement patterns via within-group configurations of role profiles and their impact on performance in collaborative problem solving," *Interactive Learning Environments*, vol. 32, no. 9, pp. 5836–5851, Oct. 2024, doi: 10.1080/10494820.2023.2239295.