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Comparing Instructional Models and Predicting Academic Performance in Physics Experiments: A Quasi-Experimental Study

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Abstract. Improving student performance and fostering higher-order abilities in physics experiment courses has long been difficult, since such courses require both conceptual mastery and hands-on problem-solving. This study has compared three instructional approaches—traditional blended learning (control group, CG), flipped classroom-based blended learning (FB), and problem-based blended learning (PB)—to evaluate their impact on the students' academic performance, critical thinking, and self-efficacy. A quasi-experimental pretest–posttest design was implemented with second-year undergraduates. The data was collected using standardised academic assessments, validated psychological scales, and behavioural learning records. The findings indicated that FB and PB produced better results than CG. FB resulted in more significant improvements in critical thinking (Cohen's d = 0.855), while PB was particularly helpful in boosting self-efficacy (Cohen's d = 0.842). The multiple regression results indicated that the behavioural indicators, including activity performance and experiment reports, strongly predict academic achievement in FB and PB. At the same time, the initial scores played a larger role in CG. Beyond statistical significance, this study

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points to clear pedagogical implications. Instructors can make blended courses more responsive and equitable by embedding behavioural learning analytics into curriculum design. The results call for a transformation in higher education, advancing dynamic, learner-centred, and personalised practices that foster innovation and equity in STEM education.

Keywords: Problem-based Learning; Flipped Classroom; Blended Learning; Academic Performance; Performance Prediction

1. Introduction

Pandemics, the digital revolution, and increased demands for flexible and fair learning are all causing significant changes in higher education worldwide. This means that old teaching paradigms need to change. These external challenges have exposed long-standing limitations in conventional teaching approaches and emphasised the urgency of developing more student-centred and adaptable forms of instruction. With the shifting landscape, university physics experiment courses are an important way to connect theory and practice, improve scientific literacy and technical skills, and get students involved in hands-on, inquiry-based learning (Pols & Dekkers, 2024). Although blended learning is becoming more common after the pandemic, many of its implementations are still superficial. Even though there are online resources to help, offline teaching is still often teacher centred. Students can often only verify experiments already set up, and they do not have many chances to explore, be creative, or think critically.

Emerging educational technologies have created new opportunities to redesign experimental instruction. Digital resources such as virtual simulations, learning management systems (LMS), and multimedia platforms facilitate more interactive and personalised learning by improving pre-class preparation, promoting cognitive engagement, and fostering peer collaboration (Kefalis et al., 2025). These technologies lay the groundwork for innovative teaching models, particularly student-centred approaches like the flipped classroom (FC) and problem-based learning (PBL). As Garrison and Vaughan (2008) argued, blended learning represents more than a mere combination of delivery modes; it requires a fundamental redesign of the teaching and learning process, grounded in collaboration, inquiry, and student agency.

This study draws on two educational theories: constructivism and cognitive load theory. As Vygotsky (1978) and Piaget (2015) described, constructivism views learning as a process of building knowledge through interaction and experience. In line with this idea, FC and PBL give students an active role, encourage questioning, and place collaboration at the centre. Cognitive load theory (Sweller, 1988) adds a practical layer. It reminds us that learning tasks must be sequenced carefully so then the pre-class preparation supports, rather than overloads, in-class application.

The FC model restructures traditional instruction by delivering core content through pre-class videos, reserving class time for active learning, peer collaboration, and real-time feedback from the instructor (Aydin & Demirer, 2022). In university physics experiments, FC encourages students to prepare adequately before class, to deeply participate in the data interpretation, to strengthen the collaborative interactions among classmates, and to obtain timely teaching feedback. PBL diverges from the traditional knowledge-centred approach by utilising real-world problems as the starting point to guide students in exploring knowledge independently and developing problem-solving skills (Hamzah et al., 2022). Applied to experimental courses, PBL fosters a deeper conceptual understanding, experimental design ability, and teamwork competence.

Previous studies have documented that FC and PBL strengthen academic performance, engagement, self-efficacy, and critical thinking, especially in mathematics, computer science, and engineering (Gong et al., 2024; Smith et al., 2022). In contrast, little attention has been paid to their effectiveness in hands-on experimental settings where the learning outcomes depend on integrating conceptual understanding with practical and collaborative skills. This gap highlights the need to examine whether blending FC or PBL with traditional models produce equal or superior educational gains in experimental science settings.

According to Daza et al. (2022), student performance is subject to psychological, academic, and demographic influences. As highlighted by Nguyen et al. (2023), examining how such variables interact with teaching models can inform more effective instructional design. Such factors can be classified into online and offline behavioural data in blended learning contexts. Existing research has primarily emphasised online behaviour metrics, with limited exploration of how online and offline behaviours jointly predict student performance. This limitation is particularly evident in flipped classroom-based blended learning (FB) and problem-based blended learning (PB) implementations in experimental courses.

Despite the growing literature on student-centred instructional models such as FC and PBL, several important research gaps remain. First, few studies have examined their role in hands-on experimental contexts like university physics experiments. Second, there is a lack of direct comparative studies between FC and PBL within the same experimental course, leaving the relative effectiveness of each approach unclear. Third, while learning analytics is increasingly applied, most studies rely on online or offline behavioural data in isolation. Few have integrated both to predict student performance in blended experimental learning environments.

The present study integrates FC and PBL into a blended learning framework for a university physics experiment course to address these gaps. It examines the effects of these approaches on the students' academic performance, critical thinking, and self-efficacy while also investigating how the students' online and offline learning behaviours contribute to academic success. Drawing upon the preceding discussion, this research aims to explore the following key questions：

RQ1: How do FB and PB significantly improve the students' academic performance, critical thinking, and self-efficacy compared to traditional blended learning (CG)?
RQ2: How do the three blended learning approaches differ in promoting the students' critical thinking and self-efficacy?
RQ3: How do the students' online and offline learning behaviours predict academic performance across different blended learning models?
In response to these inquiries, the subsequent hypotheses are put forth:
H1: Students in the FB and PB groups will significantly improve their academic performance, critical thinking abilities, and self-efficacy compared to the CG group.
H2: The CG, FB and PB groups will differ significantly in their effects on the students' critical thinking and self-efficacy.
H3: The students' online and offline learning behaviours will significantly predict their academic performance across different blended learning models.

2. Literature Review

This chapter reviews literature on blended learning in experimental physics to situate the present study within this research landscape. It first examines the impacts and gaps of blended learning in the physics and experimental contexts, then discusses two student-centred experimental instructional models (FC and PBL), and finally considers studies predicting academic performance according to the students' online and offline learning behaviours.

2.1 Impacts and Gaps of Blended Learning in Physics and Experimental Contexts

Blended learning is widely recognised to boost students' academic performance and conceptual understanding, as well as strengthening their higher-order thinking skills. As noted in recent work, it also supports personalised instruction by adapting to the students' individual learning needs (Haftador et al., 2023; Li & Wang, 2022; Tong et al., 2022).

This same positive influence carries over to physics education. Looking at the existing studies, a clear trend emerges pairing virtual or digital resources with in-person teaching does more than improve the students' grasp of physics concepts. It outperforms fully online learning in this regard. It also improves the students' self-efficacy and cognitive engagement and builds their confidence in tackling physics content (Rizaldi et al., 2021; Radulović et al., 2023). For more specialised topics like quantum physics, blended approaches have shown particular value: the 4-D blended model, for example, helps foster analytical thinking, critical reasoning, and problem-solving skills, with interactive modules and focused activities reinforcing these gains (Doyan et al., 2022; Denisova et al., 2021).

The situation in university physics experiment courses is comparable. Blended learning supports the better understanding of experimental principles, deeper involvement in inquiry-based learning, and smoother connections between online pre-class preparation and in-class hands-on work (Di Marco et al., 2009; Shao et al., 2020; Wen & Dawod, 2022). It also encourages learner autonomy and keeps instruction consistent, but researchers have pointed out a lingering issue: keeping students actively engaged with the online components throughout the experimental learning process remains a challenge (Yu & Xiang, 2023; Chithrananda & Jeewandara, 2024).

Although blended learning has enhanced student achievement, engagement, and higher-order thinking in physics education, most research has centred on lecture- or theory-based courses. Studies on its application in physics experiment courses remain limited, particularly regarding how instructional design influences cognitive and learning outcomes. This gap underscores the need to investigate blended approaches in experimental settings further.

2.2 Student-Centred Models in Experimental Physics: Flipped and Problem-Based Approaches

The FC and PBL have been progressively implemented in physics and experimental physics courses, with considerable evidence indicating that both strategies improve students' academic performance, engagement, and higher-order cognitive skills. In theoretical and experimental physics contexts, FC can enhance the students' achievement, conceptual comprehension, and problem-solving skills (Koray et al., 2023; Pattiserlihun & Setiadi, 2020; Rapi et al., 2022).

FC models incorporating hands-on activities or gamified elements in experimental settings enhance the students' motivation, experimental competencies, self-efficacy, and learning dispositions (Ahmed & Asiksoy, 2021; Gómez-Tejedor et al., 2020). FC has improved aspects of creative thinking like fluency, flexibility, and elaboration when used with creative problem-solving strategies (Rahayu et al., 2022).

PBL has also shown promise in teaching physics. Technology-supported and mobile-assisted implementations have enhanced critical thinking, self-efficacy, and engagement (Putri & Prahani, 2024; Sedayu et al., 2024). Contextual designs, including simulations and real-world problem tasks, have developed analytical reasoning, explanatory capacity, and evaluative skills (Kardoyo et al., 2020; Nurroniah et al., 2025; Pratiwi & Hariyono, 2022). In physics experiment courses, PBL-based modules have improved the students' data analysis, communication, and problem-solving skills (Adamczyk et al., 2025; Sujanem & Suwindra, 2023).

Despite the growing use of FC and PBL in physics experiment courses, their blended formats remain limited. Most studies have examined only one model in isolation, and few have systematically implemented flipped classroom-based learning (FB) or problem-based blended learning (PB). Direct comparisons of FB and PB within the same course are rare, leaving their relative benefits unclear.

2.3 Predicting academic performance from online and offline learning behaviours

Research indicates that online and offline behaviours can predict academic performance, with relatively consistent patterns across the studies undertaken to date. Indicators like online quiz participation, video engagement, and LMS activity are strong predictors of online learning. Regression models and machine learning have used this data for accurate predictions such as identifying at-risk students in physics courses or achieving reliable performance estimates (Asiksoy, 2025; Chen et al., 2020; Jiang, 2025; Rincon-Flores et al., 2022).

Recent studies highlight that combining online and offline data improves predictions more than online-only data. Methods like multiple regression (R^2=0.777) and autoregressive models (28% accuracy boost) confirm this, and early prediction is feasible—for example, estimating performance by the first semester quarter in flipped classroom-SPOC models. Even in physics experiment courses, combining both behaviours boosts accuracy from week four (Chen & Yang, 2023; Hamadneh et al., 2022; Kanetaki et al., 2022; Xu et al., 2021; Wen et al., 2025).

Despite these advances, the interaction of online and offline behaviours in predicting performance within hands-on physics experiment courses remains underexplored. Further research is needed to clarify how combined behavioural data can improve predictive accuracy and provide timely insights in experimental learning contexts.

3. Methodology

This chapter outlines the methodology used to study the effects of different instructional approaches and to construct a model to predict student performance. It begins with an introduction to the research design and a description of the participants and instructional procedures. Subsequent chapters describe the measurement methods and instruments used, detail the data collection process, and explain the analytical approaches employed.

3.1 Research Design

As shown in Figure 1, this study adopted a quasi-experimental design featuring pretest and posttest measures with a control group. It aimed to explore how three types of blended instruction impact the students' academic outcomes, higher-order thinking, and self-efficacy within the context of a university-level physics experiment course. The three instructional groups included a control group (CG) employing a traditional teacher-centred blended approach, a flipped classroom-based blended learning (FB), and a problem-based blended learning (PB).

All instructional interventions were implemented over one semester and delivered by the same instructor to ensure pedagogical consistency. Quantitative data was collected through academic assessments, validated psychometric instruments, and behavioural tracking via the online learning platform. In addition, this study employed multiple regression analysis to examine how the students' online and offline learning behaviours could predict their final academic performance across the three instructional models.

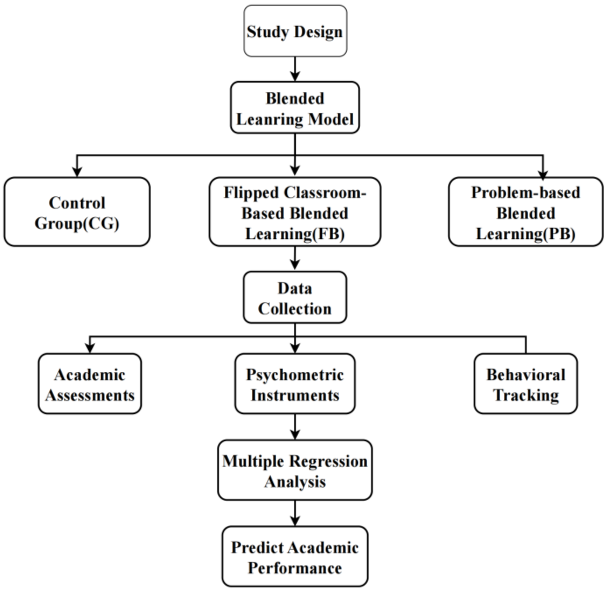

Figure 1: Study workflow for model comparison and performance prediction.

3.2 Participants

The study involved 170 second-year undergraduates from a western Chinese university who were enrolled in a compulsory university physics experiment course. The participants were drawn from five intact classes, representing the entire cohort taking this course during the semester. These students were selected because the teaching reform was implemented within the instructor's classes, ensuring that all students enrolled in the course were included without additional sampling.

The participants were assigned to one of three instructional groups: the CG group (one class, n = 34), the FB group (two classes, n = 68), and the PB group (two classes, n = 68). Due to administrative and scheduling constraints, individual-level random assignment was not feasible. Intact classes were assigned to each instructional condition, resulting in unequal group sizes. This approach reflects the natural structure of higher education teaching in the local context and supports ecological validity, although it may introduce some limitations in group comparability.

All participants had completed a university physics theory course the preceding semester, delivered by the same teaching team using consistent content and assessment standards. Based on the strong conceptual alignment between theoretical knowledge and experimental competencies, this study used the students' final college physics grades as the initial score for the experimental course. All participants carefully read and signed the informed consent form before the data collection began. Ethical approval for this study was obtained from the Research Ethics Committee of Chiang Mai University (No. 8392(10). E.1/282) and the study was conducted in accordance with institutional ethical guidelines.

3.3 Instructional Procedures

Building on the consistent instructional structure across all groups, three distinct blended learning models were implemented, differing in their teaching strategies, learner engagement levels, and interaction formats. To ensure instructional coherence, each intervention was separated into three distinct stages: pre-class, in-class, and post-class. Figure 2 visually illustrates the instructional processes for the CG, FB, and PB groups. This diagram highlights the key variations in the instructional activities, teacher-student interactions, and collaborative learning mechanisms across the three models.

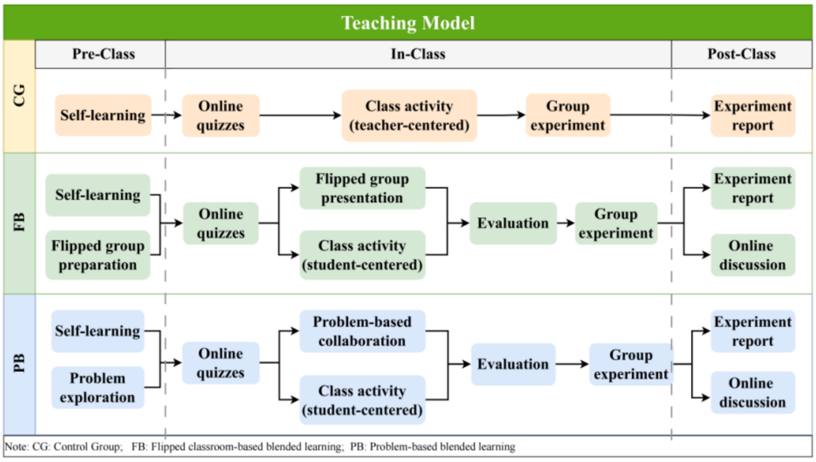

Figure 2: Phased comparison of the CG, FB and PB models

In the CG group, the students independently prepared by reviewing the teaching materials uploaded online but received no formal guidance, collaboration, or assessment. In class, the instructor demonstrated and explained the experimental steps. After class, the students submitted experiment reports without feedback or discussion. This structure reflects a typical teacher-centred blended learning model.

In the FB group, students accessed the pre-class videos and materials through the Superstar platform and could consult the instructors online as needed. Selected team members prepared and rehearsed demonstrations. Each class began with a short quiz to assess the students' preparation. Then, the flipped team led the class, explained the experimental principles, demonstrated the experimental steps, and answered their classmates' questions in real time. Their performance was evaluated by their peers and the instructor using standardised rubrics. During the experiments, flipped team members supported others as teaching assistants. After class, students submitted experiment reports and participated in online discussions.

In the PB group, students also used the Superstar platform for preparation. The instructor provided open-ended problems, and the students worked in groups to select the topics, conduct research, and prepare their presentations. Each class also began with a short quiz, followed by student-led problem statements and discussions guided by their peers and the instructor. The instructor facilitated the discussion without offering direct answers. After class, the students completed experiment reports and shared reflections on the Superstar forums.

3.4 Measures and Instruments

The impact of the instructional interventions was evaluated using three primary outcome measures: academic achievement, critical thinking disposition, and self-efficacy. Each was assessed quantitatively using validated instruments administered to all participants. This study considers critical thinking and self-efficacy as cognitive learning outcomes. Self-efficacy is occasionally associated with emotions due to its relationship with confidence, but it is part of the cognitive domain. According to Bandura (1986), self-efficacy refers to a task-specific assessment of competence. This definition firmly situates it within cognition rather than affect.

3.4.1 Academic Achievement

Student performance was evaluated using a standardised exam with two parts: (a) a theoretical test with multiple-choice and fill-in-the-blank questions evaluating physics concepts, the experimental design, and procedures; and (b) a practical task requiring students to conduct an experiment and analyse the data within a set time. All groups received the duplicate test content, and the same instructor performed the grading to ensure fairness and objectivity.

This exam format has been used for many years in school, showing that it is stable and in line with the goals of the course. The two-part structure demonstrates content validity by assessing theoretical comprehension and practical competencies simultaneously. Informal analyses of previous cohorts also showed that the test can tell the difference between different levels of student performance, which supports acceptable criterion-related validity. These features work together to ensure that the academic achievement measure is reliable and valid.

3.4.2 Critical Thinking Ability

The students' disposition toward critical thinking was measured using the Chinese version of the Critical Thinking Disposition Inventory (CTDI-CV), which was originally derived from the California CTDI and subsequently validated for use in China by Yu and Yu (2020). This instrument has been employed in various educational studies (Zheng et al., 2025; Zhu et al., 2021).

It consists of 28 items across six dimensions: Truth-seeking (3 items), Analyticity (3 items), Systematicity (5 items), Inquisitiveness (5 items), Cognitive Maturity (5 items), and Self-confidence (7 items). A 6-point Likert scale was used to capture the participants' responses. The scale showed good reliability (Cronbach's $\alpha = 0.804$) and construct validity (KMO = 0.868; Bartlett's test, $p < 0.001$). It was administered at the pre- and post-intervention stages, and changes in critical thinking disposition were assessed by calculating the gain scores.

3.4.3 Self-Efficacy

Physics-related self-efficacy was measured using the Physics Learning Self-Efficacy (PLSE) Questionnaire developed by Appiah-Twumasi et al. (2022). The 17-item scale comprises four dimensions: Everyday Application (4 items), Higher-

Order Thinking Skills (4 items), and Physics Content (4 items). Physics Practical (5 items). Responses were recorded using a 5-point Likert scale. The PLSE demonstrated good internal reliability (Cronbach's $\alpha = 0.796$) and construct validity (KMO = 0.791; Bartlett's test, $p < 0.001$). Consistent with the approach used for critical thinking, the gain scores were used to evaluate improvements in the students' confidence in handling physics tasks.

3.5 Data Collection Process

This section presents the procedures for handling the data employed to address the research questions. Based on the instructional design and learning activities described above, behavioural data and outcome measures were collected to examine learning patterns and instructional effects. Specifically, eight behavioural variables were identified including online quizzes, video viewing time, page views, initial scores, activity performance, experiment report, flipped classroom performance, and problem-solving engagement. Based on their source of collection, these variables were classified as either online or offline. Table 1 summarises the definition, characteristics, and classification of each variable.

Table 1: Variable definitions for the university physics experiment course

Code	Variables	Description	Source	Range
X_1	Online Quizzes	A weekly quiz assessing the students' pre-class preparation through multiple-choice and fill-in-the-blank questions.	Online	[0-100]
X_2	Video Viewing Time	Total time spent viewing instructional videos on the Superstar platform.		[0-1]
X_3	Page Visits	Total number of page views on the Superstar platform.		[0-1]
X_4	Initial Scores	The first-semester physics course grade served as the baseline for the academic performance evaluation.	Offline	[0-100]
X_5	Activity Performance	Score reflecting the students' participation, classroom interaction, and knowledge mastery.		[0-1]
X_6	Experiment Report	After each experiment, the students submitted an experiment report assessed for accuracy, clarity, and completeness.		[0-100]
X_7	Flipped Classroom Performance	Teacher and peer assessments of student performance in a flipped classroom.		[0-100]
X_8	Problem-Solving Engagement	Student participation in group-based experimental discussions under PBL instruction.		[0-100]

Note: The definitions of the variables remain consistent across all subsequent tables

The students completed online quizzes and submitted weekly experiment reports during the eight-week experiment course. The average scores from all eight sessions were used for the final analyses. All continuous variables (X_1–X_8) were rescaled to a [0, 1] range using min–max normalisation to eliminate scale disparities across the different measures. This normalisation ensured comparability and prevented any single variable from dominating the regression models.

3.6 Data Analysis

To comprehensively evaluate the effects of the three different instructional approaches (CG, FB, PB) on the students' academic achievements, critical thinking and self-efficacy, all data analyses were executed using IBM SPSS Statistics software (Version 25.0). Descriptive analyses were conducted initially to assess whether the baseline characteristics across the groups were comparable. The normality of the initial scores was tested using the Shapiro-Wilk method, while Levene's test was employed to examine variance homogeneity. If the assumptions were violated, Welch's analysis of variance (ANOVA) was used instead of one-way ANOVA. Tukey's Honestly Significant Difference (HSD) post hoc test was performed to identify significant group differences. To measure within-group gains from the pre-test to the post-test, the paired-sample t-test was performed.

Gain scores were used to assess critical thinking and self-efficacy changes across the groups. As these variables did not meet the normality assumption, the Kruskal–Wallis H test was used for group comparisons, followed by the Mann–Whitney U test for pairwise differences. Pearson correlation analysis examined the relationships between academic outcomes and behavioural indicators. Finally, multiple linear regression was conducted to examine the degree to which the eight behavioural variables predicted the students' final academic performance.

4. Results and Findings

This chapter reports the study's results, focusing on three aspects: the effects of instructional approaches on the students' academic performance, critical thinking, and self-efficacy; the comparative differences among the blended learning models; and the predictive role of the students' online and offline learning behaviours.

4.1 Effects of Different Instructional Approaches on Academic Performance, Critical Thinking and Self-Efficacy

This section provides a comprehensive review by first reporting the effects of the instructional approaches on the students' academic performance and then the differential impacts on critical thinking and self-efficacy.

4.1.1 Effects on Students Academic Performance

Prior to the instructional intervention, a Welch ANOVA was conducted to examine the baseline differences in the students' initial academic performance. The analysis revealed no statistically significant difference among the three groups, with Welch's being $F(2, 89.21) = 0.592$, $p = 0.590$, indicating comparable baseline scores across the instructional conditions.

Following the intervention, the paired-sample t-test (see Table 2) confirmed that all three groups achieved statistically significant improvements in their final scores. However, the PB and FB groups showed greater score increases than the CG group. Figure 3 also shows this pattern clearly, with both experimental groups showing steeper rising trajectories from the pretest to the posttest. The shaded bands represent 95% confidence intervals, indicating that the performance gains observed in the PB and FB groups were larger and more consistently reliable compared to the control condition.

Table 2: Descriptive statistics and within-group paired-sample t-test initial and final scores

Group	N	Initial Scores (Mean ± SD)	Final Scores (Mean ± SD)	Mean Diff	t(df)
CG	34	76.91 ± 7.74	81.08 ± 6.94	4.18	3.16(33) **
PB	68	77.65 ± 7.85	86.67 ± 5.57	9.03	8.76(67) ***
FB	68	75.93 ± 12.19	85.55 ± 6.58	9.62	7.15(67) ***

** p<0.05 ** p<0.01 *** p<0.001*

Before conducting the between-group analyses, normality and variance homogeneity tests were performed, and both assumptions were met ($p > 0.05$). Therefore, a one-way ANOVA was conducted to examine whether the type of instructional model significantly influenced the students' final performance. The analysis revealed a statistically significant difference among the three groups, $F(2, 167) = 8.89$, $p < 0.001$. The Post-hoc Tukey test (Table 3) indicated that both the PB ($p<0.001$) and FB ($p=0.003$) groups significantly outperformed the CG group, while no significant difference was found between the PB and FB groups ($p = 0.539$). These findings suggest that FB and PB approaches are more effective than traditional blended instruction in enhancing the students' academic performance.

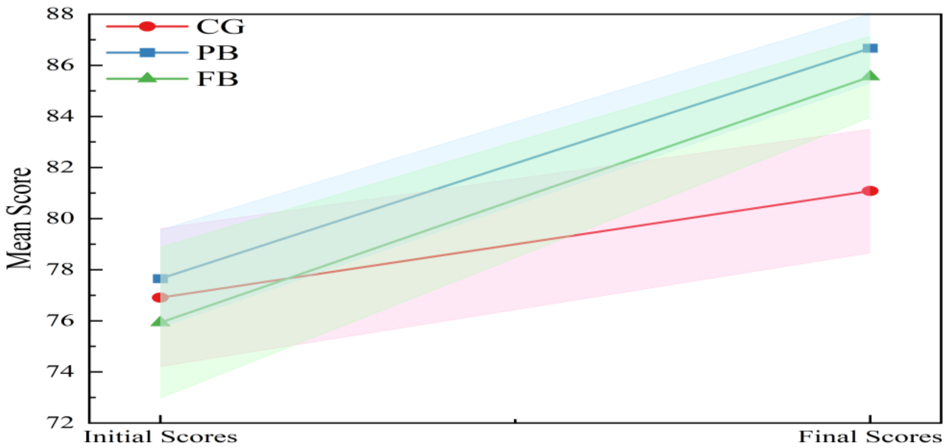

Figure 3: Interactions according to group and pre/posttest with academic performance

Table 3: Post-Hoc Tukey Test for the Final Scores Among the Groups

Comparison	Mean Difference	95%CI	P-value
PB vs. CG	5.59	[2.41,8.77]	0.000
FB vs. CG	4.46	[1.31,7.61]	0.003
PB vs. FB	1.13	[-1.38,3.63]	0.539

4.1.2 Differential Impacts on Critical Thinking and Self-Efficacy

Due to incomplete or invalid questionnaire responses, the number of valid paired samples differed slightly across groups. For critical thinking, valid cases included 28 in the CG group, 58 in the FB group, and 64 in the PB group. For self-efficacy, the respective numbers were 30, 61, and 64.

As the difference scores were not normally distributed, the Wilcoxon signed-rank test was conducted to examine the within-group differences in critical thinking and self-efficacy before and after the interventions. As presented in Table 4, the CG group showed no meaningful change in either critical thinking ($p = 0.243$,) or self-efficacy ($p = 0.068$), indicating that traditional instruction had a limited impact on these outcomes.

In contrast, the FB and PB groups demonstrated statistically significant improvements (all $p < 0.001$). For critical thinking, PB improved by about 12.5 points and FB by about 11 points, with FB ultimately achieving a slightly higher post-test level. Regarding self-efficacy, PB showed a much larger gain of about 18.5 points compared to 9 points in FB, highlighting the more substantial effect of problem-based learning on these skills. These patterns are evident in Figure 4. Both interventions produced upward trajectories relative to the CG, with broadly comparable gains in critical thinking but a markedly steeper slope for PB in self-efficacy. These findings suggest that both FB and PB approaches are more effective than traditional instruction in improving the students' critical thinking and self-efficacy.

Table 4: Intra-group comparisons of critical thinking and self-efficacy before and after the interventions

Variables	Group	N	Median (Pre)	Median (Post)	Z-value	Effect size(r)
Critical thinking	CG	28	109.00	109.00	1.167	0.221
	PB	64	103.00	115.50	6.359***	0.795
	FB	58	109.00	120.00	6.515***	0.855
Self-efficacy	CG	30	77.00	83.00	1.828	0.334
	PB	64	78.50	97.00	6.739***	0.842
	FB	61	75.00	84.00	6.341***	0.812

Note: Effect size calculated as $r=Z/\sqrt{N}$. *$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$*

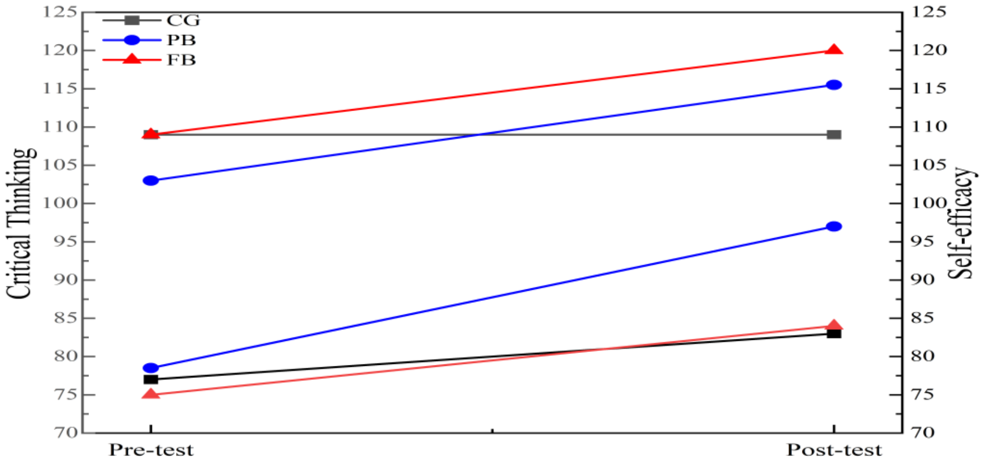

Figure 4: Median scores for critical thinking and self-efficacy (pre- and posttest)

Note: The left Y-axis represents the critical thinking scores, while the right Y-axis represents the self-efficacy scores.

4.2 Differences of the three blended learning approaches in promoting student critical thinking and self-efficacy

This section presents the results that address RQ2. The analysis focuses on two outcomes: critical thinking and self-efficacy, with the latter treated as a cognitive construct in this study.

As the gain scores for critical thinking and self-efficacy did not meet the normality assumption, the Kruskal–Wallis H test was employed to examine overall group differences. The results revealed statistically significant differences across the three instructional groups in both outcome domains: critical thinking ($H = 25.777$, $p < 0.001$) and self-efficacy ($H = 17.645$, $p < 0.001$). These findings suggest that the blended learning approaches had differential effects on the students' cognitive development. Given the above results, pairwise comparisons were performed using the Mann-Whitney U test to determine differences at the specific group level. Table 5 presents the median values, test statistics, and effect sizes (r).

The results show that both FB and PB significantly outperformed CG in critical thinking ($p < 0.001$), with effect sizes ranging from moderate to large ($r = 0.466$–0.518). However, no significant difference was found between the PB and FB groups ($p = 0.593$), suggesting a comparable improvement in critical thinking between the two instructional models. For self-efficacy, PB significantly outperformed both CG ($p < 0.001$, $r = 0.448$) and FB ($p = 0.018$, $r = 0.206$), indicating a more substantial effect on the students' self-perceptions. FB also showed significantly higher gains than CG ($p = 0.016$, $r = 0.234$), although the effect was negligible.

Table 5: Pairwise comparisons of group gains in critical thinking and self-efficacy

Variable	Comparison	Median (Md)	Z-value	Effect Size(r)
Critical thinking	PB vs CG	6.50 vs 2.00	-4.472***	0.466
	FB vs CG	9.00 vs 2.00	-4.801***	0.518
	PB vs FB	6.50 vs 9.00	-0.534	0.048
Self-efficacy	PB vs CG	12.00 vs 4.00	-3.997***	0.412
	FB vs CG	6.00 vs 4.00	-2.414*	0.253
	PB vs FB	12.00 vs 6.00	-2.365*	0.212

Figure 5 shows these trends using comparison box plots. The CG group exhibited minimal enhancement in both constructs, whilst FB and PB attained significantly greater advancements. In critical thinking, FB and PB performed similarly and distinctly outperformed CG. A sequential pattern in self-efficacy was seen (PB > FB > CG), underscoring the greater influence of problem-based learning. Letters above the boxes (a, b, c) indicate group differences: identical letters denote no significant difference, different letters indicate p < 0.05.

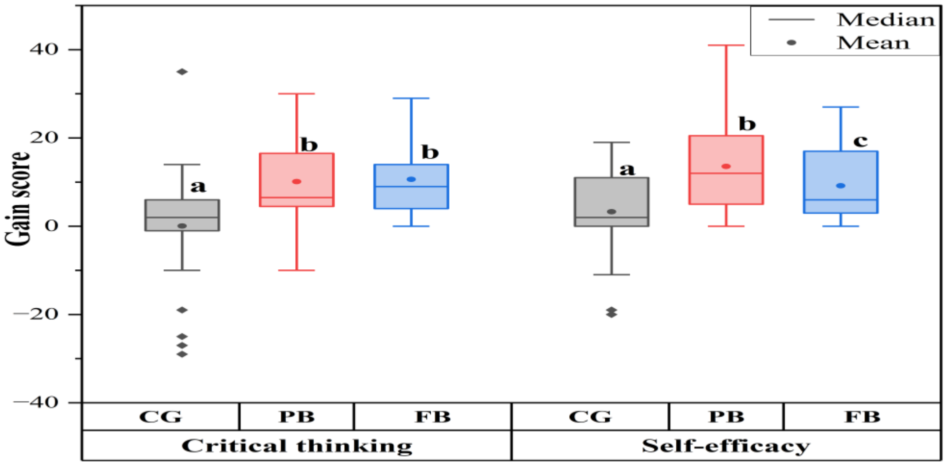

Figure 5: Instructional method effects on critical thinking and self-efficacy gain scores

In summary, the FB and PB groups outperformed the CG group in critical thinking and self-efficacy. Although the fundamental thinking improvements were similar for FB and PB, PB's self-efficacy improved the most.

4.3 Students' online and offline behaviours and their academic performance across the different blended learning models

Academic achievement is a critical outcome in education research, and understanding its influencing factors is vital for improving instruction. This study examines how the students' online and offline behaviours predict their academic performance.

4.3.1 Correlation Between Learning Behaviours and Academic Performance

Pearson correlation analyses were conducted for the CG, FB, and PB teaching models to examine the relationships between student learning behaviours (X_1–X_8) and their final academic performance. The correlation patterns varied notably across the instructional models (Figure 6).

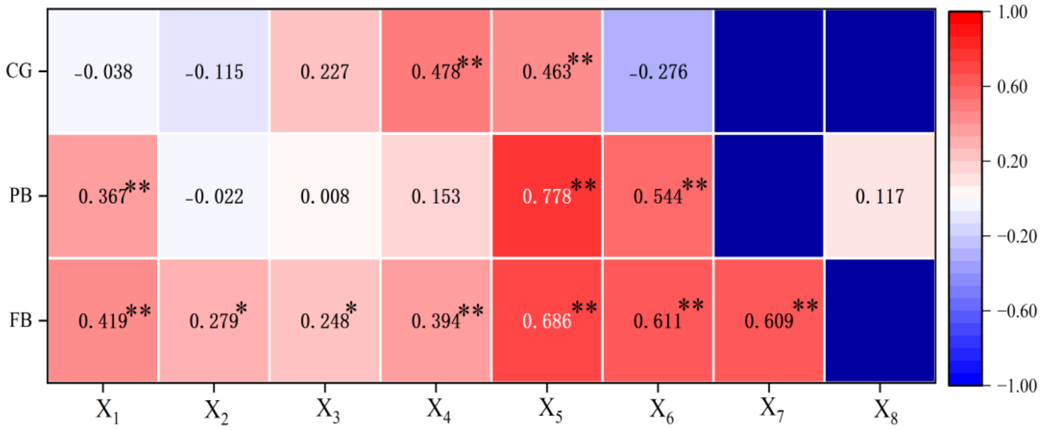

Figure 6: Pearson correlation heatmap between learning behaviours and academic performance (* p<0.05, **p<0.01)

In the FB group, most behavioural indicators were moderately to highly positively correlated with the final academic performance. Notably, online quizzes (X_1) (r=0.419**), initial scores (X_4) (r=0.394**), activity performance (X_5) (r = 0.686**), experiment report (X_6) (r = 0.611**), flipped-classroom performance (X_7) (r = 0.609**) were strongly correlated with the student's final score, highlighting the importance of engagement and peer explanation in a flipped learning environment.

For the PB group, the most predictive variable was again activity performance (X_5) (r = 0.778**), followed by the experiment report (X_6) (r = 0.544**) and online quizzes (X_1) (r=0.367**). Problem-solving engagement (X_8) scores showed only a weak correlation (r = 0.117, p = 0.117). This suggests that although group inquiry promotes active learning, its effectiveness may be influenced by additional factors such as the quality of facilitation or the students' preparedness. In contrast, the CG group showed fewer and weaker significant correlations. Initial scores (X_4) (r = 0.478**) and activity performance (X_5) (r = 0.463**) were the only predictors significantly associated with the outcome. Surprisingly, the experiment report (X_6) showed a negative correlation (r = -0.276), which may indicate that despite submitting reports, the students were still less engaged, or the reports were of a lower quality.

4.3.2 Multiple Regression Analysis for Performance Prediction

Multiple linear regression analyses were employed for each instructional group to further explore the predictive strength of behavioural variables. Before regression, the variance inflation factors (VIF) values were examined and observed to be below 5, indicating no multicollinearity. Table 6 lists each teaching condition's standardised regression coefficients (β) and model fit indices (R^2 and adjusted R^2). Figure 7 compares the standardised beta values and their 95% confidence ranges, as well as each predictor's relative importance, and direction (positive or negative).

Table 6: Predictive effects of student learning behaviours on their final performance in the three instructional models

Variables	CG(β)	PB(β)	FB(β)
X_1	0.080	-0.005	0.196**
X_2	0.022	-0.018	-0.050
X_3	0.173	-0.078	0.075
X_4	0.543**	0.127	-0.099
X_5	0.403**	0.704**	0.571**
X_6	-0.304*	0.378**	0.335**
X_7	— —	— —	0.295**
X_8	— —	0.142*	— —
R^2	0.564	0.788	0.824
Adjust R^2	0.459	0.763	0.804

Note: 95% confidence intervals are visually presented in Figure 7. * $p<0.05$ ** $p<0.01$ *** $p<0.001$

In the CG group, three predictors contributed significantly to the model. The initial score (X_4) (β = 0.543**) and activity performance (X_5) (β = 0.403**) were significantly positively correlated with the final score. In contrast, the experiment report (X_6) had an adverse effect (β = −0.304*). The model explained approximately 45.9% of the variance in student performance (adjusted $R^2 = 0.459$). For the PB group, activity performance (X_5) (β = 0.704**), experiment report (X_6) (β = 0.378**), and problem-solving engagement (X_8) (β = 0.142, $p < 0.05$) significantly predicted the final scores. The model yielded an adjusted R^2 of 0.763.

In the FB group, four variables were statistically significant: activity performance (X_5) (β = 0.571**), experiment report (X_6) (β = 0.335**), online quizzes (X_1) (β = 0.196**), and flipped classroom performance (X_7) (β = 0.295**). This model accounted for 80.4% of the variance in the students' final scores (adjusted R^2 = 0.804), indicating excellent predictive capacity.

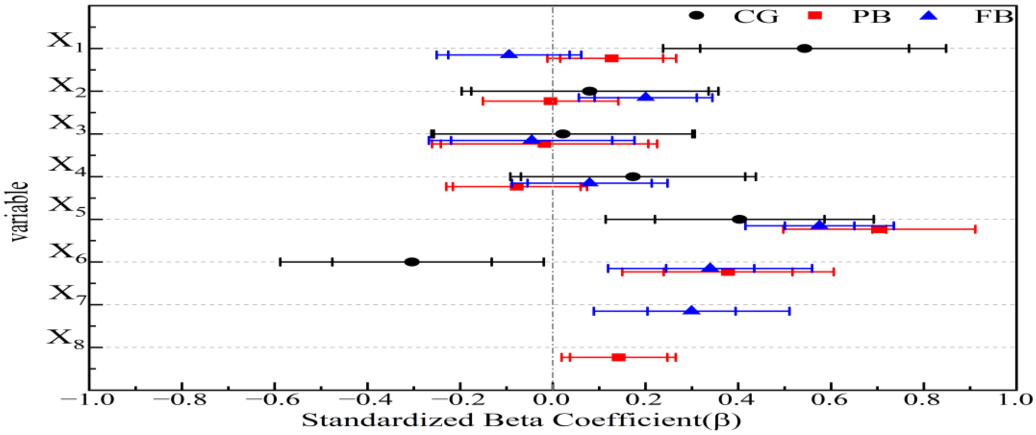

Figure 7: Forest plot of the standardised coefficients and 95% confidence intervals across the instructional models

To evaluate model accuracy, the predicted scores were plotted against the actual scores for each instructional group (Figure 8). The dashed diagonal line (y = x) represents a perfect prediction, where the predicted score matches the actual score. Data points close to this line indicate higher predictive accuracy, whereas larger deviations from the line indicate greater prediction errors.

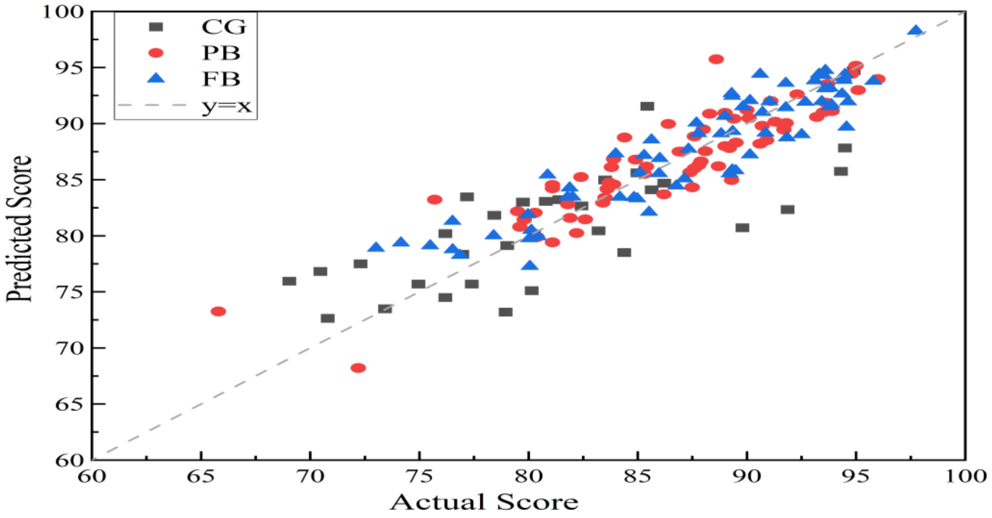

Figure 8: Comparison of the predicted and actual final scores across the three instructional groups

The FB and PB groups generally show a tighter distribution of points along the diagonal line. The FB group in particular shows minimal deviation across both low- and high-performance ranges. In comparison, the CG group exhibits a wider spread of data points, especially at the lower and upper ends of the scale. This pattern reflects greater variability in prediction accuracy under the CG model. In all three instructional models, academic performance was significantly predicted by a combination of online and offline learning behaviours. The FB and PB models yielded higher predictive accuracy than the CG model.

5. Discussion

This chapter discusses the study's findings in light of the existing research. It addresses the effects and comparisons of blended learning models (CG, FB, PB), explains the differential impacts on critical thinking and self-efficacy, and examines the role of online and offline learning behaviours as predictors of academic achievement.

5.1 Effects and Comparisons of Blended Learning Models on Academic Performance, Critical Thinking and Self-efficacy

Responding to RQ1 and H1, the results confirm that both the FB and PB models significantly outperform the CG in promoting the students' academic performance, critical thinking, and self-efficacy. As shown in Table 2, students in the FB and PB groups achieved higher final scores than those in the CG group, with large effect sizes and statistically significant gains supported by the paired-sample t-test and post hoc analyses (Tables 2 and Figure 3). These results reinforce the prior concerns about the limitations of traditional instruction in fostering engagement and deeper learning (Behmanesh et al., 2022). They are also in line with the prior research on blended learning in STEM. Through active participation in class and pre-class preparation, FB promotes deeper conceptual understanding and engagement (Baig & Yadegaridehkordi, 2023). Similarly, PB promotes meaningful learning by presenting students with real-world, challenging issues, supporting independent study, and fostering group problem-solving (Sugiyanti et al., 2023).

Table 4 confirms that FB and PB substantially enhanced the students' critical thinking and self-efficacy, which is consistent with the results from recent meta-analyses. Ezeh et al. (2022) and Luciana et al. (2024) have shown that FC approaches promote academic achievement and foster higher-order thinking skills. Similarly, Wijnia et al. (2024) and Suciana and Sausan (2023) point to the motivational and performance-related benefits of PBL across diverse educational settings.

The findings indicate that collaborative learning, formative feedback, and learner autonomy—common components of both instructional models—could be more significant in enhancing learning outcomes than the particular instructional model used. The findings are consistent with the prior research that emphasises the motivational and cognitive advantages of student-centred instructional methods (Amarilla et al., 2022; Woods & Copur-Gencturk, 2024) and underscores the significance of engagement and peer interaction in fostering more profound and more enduring learning outcomes (Pan et al., 2025).

5.2 Explaining the Differential Impacts of FB and PB on Critical Thinking and Self-Efficacy

This section compares the effects of the FB and PB models on the students' critical thinking and self-efficacy in response to RQ2 and H2. Both models improved the outcomes compared to the CG group. The Mann–Whitney U test (Table 5) showed that the two models have different cognitive results strengths.
Specifically, while both FB and PB models significantly enhanced critical thinking and self-efficacy compared to the CG group, PB demonstrated a stronger impact on self-efficacy, whereas FB showed a slight edge in improving critical thinking. These findings suggest that the two models may differ in their underlying mechanisms and areas of emphasis.

The differential effects can be further analysed through the framework of relevant theories. Based on constructivist theory, both FB and PB support students' active knowledge construction but with different emphases. PB emphasises collaborative inquiry, social interaction, and authentic problem-solving, effectively boosting the students' confidence and motivation, while FB prioritises cognitive engagement through a "pre-class preparation" in-class activity sequence. This arrangement aligns with cognitive load theory (Sweller, 1988), which posits that reducing the external cognitive load promotes deeper cognitive processing, enhancing the learning outcomes (Gong et al., 2024; Chen et al., 2025).

The following aspects can explain why PB has a more substantial impact on self-efficacy. First, PB encourages students to independently solve real-world problems, thereby gaining rich practical experience, which Bandura (1986) believes is the most potent source of self-efficacy. Second, PB assignments necessitate collaborative group work, offering verbal support and peer modelling opportunities, enhancing the students' self-confidence (Ilahi et al., 2024; Yu & Zin, 2023). Third, through continuous trial-and-error reflection, students can recognise their own growth and internalise their successes—a key path to improving perceived competence (Marthaliakirana et al., 2022).

Overall, the results show the trend that the success of blended learning may depend on how well its instructional design matches the intended goals. Suppose the goal is to improve critical thinking. In that case, the FB model may be more appropriate, whereas if the focus is on improving self-efficacy and practical application, the PB model is more suitable.

5.3 Online and Offline Learning Behaviours as Predictors of Academic Achievement

The findings strongly support RQ3 and H3. The students' online and offline learning behaviours can predict their final academic performance, and there are significant differences across the instructional approaches. Offline behaviours, particularly activity performance (X_5) and experiment reports (X_6), consistently emerged as significant predictors of final academic performance across all three teaching models, highlighting the essential role of behavioural engagement in promoting academic success (Liu et al, 2024).

In the FB and PB groups, both X_5 and X_6 were positively and significantly associated with academic achievement (FB: $\beta = 0.571^{**}, 0.335^{**}$; PB: $\beta = 0.704^{**}, 0.378^{**}$), indicating that student-centred pedagogies transform these offline tasks into meaningful learning experiences. According to constructivist theory, this pedagogical approach promotes knowledge construction through collaboration, reflective, and dialogic interaction processes validated by recent empirical studies (Brundage et al., 2023).

Conversely, with the CG group, although activity performance remained predictive ($\beta = 0.403^{**}$), experiment reports were negatively associated with final scores ($\beta = -0.304^{*}$). This suggests that students may treat experiment reports as a procedural or formal requirement rather than an opportunity for reflective learning. Without proper integration into the instructional process, the report task may impose an additional extraneous cognitive load, diverting attention and cognitive resources away from meaningful learning activities. This interpretation is supported by cognitive load theory, which emphasises that poorly integrated tasks can increase cognitive burden and interfere with knowledge acquisition (Tabatabaee et al., 2024; Timothy et al., 2023).

Online quizzes(X_1) showed more selective predictive effects, predicting performance only in the FB group ($\beta = 0.196^{**}$) by providing timely evaluations and enabling students to recognise areas of proficiency and improvement (Ouatik et al., 2022). Other online indicators, such as video viewing time (X_2) and page views (X_3), were insignificant in any group. This may be attributed to the operationalisation of these variables as they only reflect access frequency rather than the depth of interaction. These results reinforce that academic performance cannot be improved if students are not actively involved in the interaction (Sailema, 2021).

It is worth noting that the initial score (X_4) showed significant predictive power only in the CG group ($\beta = 0.543^{**}$). This suggests that in a teacher-centred teaching environment, the students' academic performance dominates. Learning achievements in this environment usually rely more on the students' existing knowledge rather than the auxiliary role provided by teaching support. Similar results were found by Delahay et al. (2023), who declared that initial score were the strongest predictor of learning gains in traditional physics courses. By contrast, student-centred models like the FC and PBL appear to mitigate the influence of prior knowledge by creating more inclusive, interactive, and collaborative learning environments. These settings allow students to meaningfully participate in the learning process, regardless of their starting point (Li et al., 2024; Salazar et al., 2023; Shao et al., 2024).

Flipped classroom performance (X_7) measured by peer and teacher evaluations of the students' group preparation and in-class performance significantly predicted the final scores in the FB group ($\beta = 0.295^{**}$). This suggests that the quality of the students' active participation in flipped sessions, both before and during class, plays an essential role in the learning outcomes. Yan et al. (2024) similarly found that students who engaged seriously in pre-class tasks and in-class activities achieved better academic results in flipped STEM courses. Additionally, problem-solving engagement (X_8) had a small but still significant effect in the PB group ($\beta = 0.142^{*}$), reflecting the importance of sustained collaborative problem-solving in authentic learning contexts a cornerstone of the PB approach.

Supporting this view, Rosyida and Prahani (2025) reported that structured group problem-solving activities significantly improved students' conceptual understanding and critical thinking in physics education, especially when supported by mobile learning tools. Overall, these results demonstrate that in a student-centred environment, learning behaviours—whether specific to FB and PB or shared offline activities in both models—are associated with academic performance and actively contribute to academic achievement. Their effectiveness is influenced by instructional design, which supports motivation, reflection, teamwork, and adaptive learning.

6. Conclusion

This study demonstrates the potential of student-centred blended learning models to enhance learning in experimental science courses. Both flipped classroom-based blended learning (FB) and problem-based blended learning (PB) approaches create conditions that shift the basis of achievement from prior knowledge toward active engagement. These models, which strongly emphasise pre-class preparation, group projects, and formative evaluation, are consistent with constructivism and cognitive load theory, which holds that organised design lowers needless cognitive demands and encourages deeper learning.

The findings highlight the central role of behavioural engagement—particularly active participation and reflective tasks—in shaping students' cognitive and affective development. From an instructional perspective, this suggests that well-designed blended learning improves achievement and supports equity by enabling students from varied backgrounds to benefit from shared active learning opportunities.

Future research should validate these findings across different STEM subjects and international contexts. Cross-cultural and multi-institutional research is required to test the validity of the FB and PB models outside of a single Chinese university. These kinds of partnerships would make it clearer how the contextual elements, such as curriculum design and cultural perspectives on teamwork, affect results. Incorporating behavioural learning analytics into these initiatives may improve equity and adaptive feedback. These student-centred models can continue to be successful and scalable in various contexts with wider international validation.

7. Conflict of Interest

The authors have no competing interests to declare that are relevant to the content of this article.

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