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Interdisciplinary Research Integration in Higher Education: A Case Study on the Development of an AI-Based Non-Invasive Hemoglobin Detection System

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Abstract: This study examines the effectiveness of Project-Based Learning (PBL) in the development of a non-invasive hemoglobin detection system using photoplethysmography (PPG) integrated with artificial intelligence. A quasi-experimental design was applied to 26 Electrical Engineering students enrolled in Big Data Analysis, Sensor Design, and Embedded Systems courses. Students worked in groups to design, implement, and test prototypes. Data were collected through project rubrics, questionnaires, observations, and reflections, and were analyzed to determine the effectiveness index. The results revealed an overall effectiveness index of 3.8, categorized as good. The highest score was achieved in the affective aspect (4.2), reflecting strong motivation, proactive attitudes, and teamwork. Cognitive (3.9) and reflection (3.8) aspects also showed positive outcomes, while psychomotor (3.6) and product quality (3.5) remained weaker due to technical issues, including prototype accuracy and troubleshooting difficulties. The study demonstrates that PBL effectively integrates theory and practice, enhances 21st-century skills, and fosters meaningful learning experiences. Additionally, the findings highlight the potential of incorporating advanced technologies into engineering education while contributing to innovative health technology solutions for addressing malnutrition.

Keywords: Hemoglobin detection; Photoplethysmography**;** Project based learning

Introduction

Project-based learning (PBL) provides a robust framework for integrating critical thinking, problem-solving, and collaboration through the development of tangible products such as electrical systems and microcontroller-based devices in engineering education (Haryudo et al., 2021; Nuri et al., 2023; Yanti et al., 2023) In this context, projects are designed not only to deepen students' understanding of engineering concepts but also to address real-world societal challenges, including public health issues (Ariyani et al., 2025; Haryudo et al., 2021; Lestari et al., 2024; Ruiz Viruel et al., 2025; Tang et al., 2024; Yanti et al., 2023). One persistent problem in many developing countries is malnutrition, including iron-deficiency anemia, which disproportionately affects children and pregnant women and has long-term consequences for quality of life and productivity (Cholidah et al., 2023; Darmoutomo, 2023; WHO, 2020) Consequently, the development of electronic devices and smart monitoring systems within a PjBL framework for early detection or education related to nutritional status is highly relevant as an interdisciplinary approach that bridges electrical engineering and public health (Darmoutomo, 2023; Yanti et al., 2023).

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This condition is caused by iron deficiency and is a major indicator of chronic malnutrition (kemenkes RI, 2023) and Indonesia ranks 73 out of 116 countries according to the (Global Hunger Index, 2021, 2023). Approximately 42% of children under 5 years of age suffer from anemia, while WHO data report a prevalence of 40% (Manikam, 2021).

Current malnutrition detection often relies on invasive methods such as laboratory blood tests using automated hematology analyzers or hemoglobinometers. However, these methods require adequate healthcare facilities, are expensive, and can be uncomfortable for patients. Furthermore, invasive methods are difficult to implement in remote areas or emergency situations, preventing rapid and efficient detection (Lara-pompa et al., 2020).

Advances in artificial intelligence, particularly deep learning (DL) and machine learning (ML), have driven innovation in malnutrition detection systems. Several studies over the past five years have demonstrated the effectiveness of DL/ML in classifying children's nutritional status through facial images (Ankalaki et al., 2024; Yunidar et al., 2025) and malnutrition detection using deep learning (Salari et al., 2025; Sulosaari et al., 2025; Widanti et al., 2023). PPG signal extraction for fatigue detection with LSTM (Yu et al., 2024), in other cases for web application security by using the LSTM algorithm (Muttaqin & Sudiana, 2024), nutritional value detection using LSTM and providing healthy food recommendations (Azmi et al., 2023; Santoso et al., 2025), and PPG signal extraction (De Palma et al., 2025; Feli et al., 2025; Filho et al., 2024; Jeon & Kang, 2023; Ngoc-Thang et al., 2022; Samann & Schanze, 2024). Interestingly, this technological development can be integrated into PBL (project-based learning) courses in electrical engineering. Students can design a microcontroller- and AI-based malnutrition detection system directly as part of a learning project, thereby strengthening reasoning skills while providing real-world solutions for the community. Research like this not only supports engineering learning outcomes but also contributes to national efforts to combat malnutrition through technology.

In this context, we examine the effectiveness of project-based learning focused on detecting anemia levels using photoplethysmography (PPG), which detects changes in blood volume through light. By integrating this technology with machine learning (Abuzairi et al., 2024; Hartana et al., 2024), the measuring system can achieve higher accuracy, making it an efficient tool to support rapid and real-time detection of malnutrition (Jones et al., 2019). There is also malnutrition detection by utilizing AI DNN and IoT edge devices (Bitew et al., 2022; Hemo, & Rayhan, 2021; Maricris, 2023; Mayrohmah et al., 2024), approaches with deep learning methods, SVR regression algorithm, LASSO, and Linear Regression techniques (Kavsaoılu et al., 2015; Thirumalraj et al., 2020; Acharya et al., 2020), as well as Multivariate Partial Least Square (PLSR) to predict Hb concentration and validate the system using Bland-Altman analysis (Pinto et al., 2021). Some studies have also designed IoT-based systems to detect hemoglobin non-invasively (Nidianti et al., 2019).

The focus of this research is to explore and analyze in depth the effectiveness of project-based learning (PBL) in the context of developing a non-invasive hemoglobin level detection system. This system utilizes photoplethysmography (PPG) techniques integrated with artificial intelligence, primarily through the application of machine learning and deep learning methods. This research aims not only to assess students' ability to combine theory and practice through complex health technology projects, but also to investigate the extent to which this interdisciplinary approach can improve the accuracy, efficiency, and real-time detection of hemoglobin levels, which are important indicators in managing malnutrition. Thus, this research makes a significant contribution to the development of advanced technology-based electrical engineering curricula while simultaneously supporting innovative solutions to critical public health problems.

Method

Research Design

This study implemented a one-group pretest–posttest design within a Project-Based Learning (PBL) setting in an electrical engineering course. In this course, a single cohort of students engaged in learning activities that combined theoretical instruction with hands-on practice by developing a non-invasive hemoglobin monitoring system based on photoplethysmography (PPG) and artificial intelligence techniques (machine learning/deep learning). The research procedure comprised two principal phases. In the instructional phase, students' knowledge, skills, and attitudes toward PBL and the developed system were assessed before and after the intervention to determine the learning effectiveness. In the system evaluation phase, the hemoglobin detection device was examined using a predefined validation protocol that involved testing on human participants, comparing its readings with those obtained from a standard hematology analyzer, and calculating performance indicators such as accuracy, precision, sensitivity, and specificity to determine the robustness of the proposed system.

Research Subjects and Locations

The research subjects were 26 students enrolled in the Electrical Engineering Study Program at Jayabaya

University who were taking the Big Data Analysis, Sensor Design, and Embedded Systems courses in the current semester. The study was conducted in the Instrumentation Laboratory and regular lecture classrooms. Given the relatively small and homogeneous sample (N = 26) and the fact that all participants were engineering students, the data obtained in this study are intended primarily to explore students' learning experiences and the feasibility of implementing the project-based learning approach in an educational setting. The sample size and population characteristics are not sufficient for drawing statistically robust conclusions about the clinical performance or generalizability of the hemoglobin detection system in real healthcare environments.

Research Process and Planning

This study was implemented using a Project-Based Learning (PBL) approach, structured into several sequential stages. At the planning stage, students were organized into small project teams and assigned a design challenge in the form of a case study. Each team was required to develop a conceptual design for a malnutrition detection system that integrates sensor technology with artificial intelligence methods. Through this activity, students identified user needs, defined system requirements, and outlined the architecture of a sensor-based and AI-driven solution for malnutrition screening.

Implementation of PBL

Discussion of literature and basic theory, preparation of conceptual design (hardware and algorithm), and presentation of design results by groups. The project activities in this study consisted of literature review and exploration of fundamental theories, followed by the conceptual design of the hardware and signal-processing algorithm, and concluded with group presentations of the resulting system design. In the algorithm development stage, an artificial intelligence model based on a Long Short-Term Memory (LSTM) architecture was implemented to analyze photoplethysmography (PPG) signals for anemia-related pattern recognition. The LSTM model was trained using PPG data collected from participants under standardized measurement procedures, where each recording was paired with reference hemoglobin values obtained through laboratory examination and subsequently labeled as anemic or non-anemic according to established clinical thresholds. This dataset was divided into training, validation, and testing subsets to develop and evaluate the model's performance, thereby providing a verifiable basis for the AI-based claim presented in this work.

Evaluation

Students were assessed based on a PBL rubric that includes collaboration skills, innovation, critical reasoning, and integration of theory with application.

Research instruments

These instruments were used to assess student performance in terms of knowledge, skills, and attitudes, as shown in Table 1 (Assessment Rubric).

Table 1. Assessment Rubric

Roadmap Stage	Focus of assessment	Indicator	Assessment method	Weight (%)
Stage 1: Initial Planning & Understanding	Basic knowledge & readiness	Understanding the concept of hemoglobin, sensors, algorithms; project proposal	Pre-test, written proposal	20
Stage 2: Technical Implementation (Design–Build–Test)	Technical skills & problem solving	Schematic design, hardware assembly, software integration, troubleshooting	Observation, skills rubric, logbook	30
Stage 3: Collaboration & Attitude (Soft Skills)	Cooperation, communication, motivation	Individual contribution, team communication, proactive attitude	Peer assessment, reflection journal, attitude questionnaire	15
Stage 4: Final Product & Validation	Prototype quality & innovation	Tool functionality, measurement accuracy, design innovation	Device performance testing, medical validation, product rubric	20
Stage 5: Reflection, Presentation & Final Evaluation	Integration of knowledge & reflection	Final report, presentation skills, learning reflection	Group presentations, final reports, reflective discussions	15

Questionnaire

In order to evaluate students' competency development after participating in the PBL-based project, a structured questionnaire was administered. The instrument consisted of items grouped into cognitive, psychomotor, product, affective, and reflection aspects. All items were rated using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The items were formulated to capture students' self-assessed ability to perform specific tasks (e.g., explaining concepts, designing and assembling the system, implementing the LSTM algorithm, troubleshooting, and reflecting on their learning), rather than merely measuring general feelings of satisfaction or confidence. The questionnaire is presented in Table 2.

Table 2. Questionnaire

Aspect	Item	1	2	3	4	5
Cognitive	After completing this PBL project, I can correctly explain the concept of hemoglobin and non-invasive detection.	☐	☐	☐	☐	☐
Cognitive	I am able to describe the working principle of the optical sensor used in the non-invasive hemoglobin system.	☐	☐	☐	☐	☐
Cognitive	I can interpret PPG signal patterns that are relevant to hemoglobin estimation.	☐	☐	☐	☐	☐
Psychomotor	I am able to design a non-invasive hemoglobin detection circuit according to given functional specifications.	☐	☐	☐	☐	☐
Psychomotor	I am able to assemble and wire the sensor, microcontroller, and supporting components correctly without assistance.	☐	☐	☐	☐	☐
Psychomotor	I can implement and run the LSTM-based AI algorithm on the device to process PPG signals.	☐	☐	☐	☐	☐
Psychomotor	I am able to troubleshoot and fix common hardware or software errors that occur in the prototype.	☐	☐	☐	☐	☐
Product	The prototype developed by my team meets the predefined functional requirements for non-invasive Hb detection.	☐	☐	☐	☐	☐
Product	The measurement results of the prototype are sufficiently consistent when tested repeatedly under similar conditions.	☐	☐	☐	☐	☐
Product	The prototype demonstrates potential applicability in real healthcare or screening settings.	☐	☐	☐	☐	☐
Affective	I actively took responsibility for technical tasks (design, implementation, testing) during the PBL project.	☐	☐	☐	☐	☐
Affective	I was willing to improve my work based on feedback from teammates or instructors.	☐	☐	☐	☐	☐
Reflection	I can identify specific technical skills that improved because of this PBL project.	☐	☐	☐	☐	☐
Reflection	I can explain how the PBL project helped me become more prepared for engineering tasks in real practice.	☐	☐	☐	☐	☐

Score Description: 1 = Strongly Disagree (STS); 2 = Disagree (TS); 3 = Neutral (N); 4 = Agree (S); 5 = Strongly Agree (SS)

Used to record student participation and obstacles that arise during the learning process.

Effectiveness Index

The effectiveness index in this study was calculated using weighted mean scores derived from the evaluation instruments. The scores used in this index are clearly distinguished into two types: (1) objective scores from the performance assessment rubric (Table 1), which measure students' cognitive and psychomotor competencies as well as the quality of the developed prototype, and (2) self-report scores from the perception questionnaire (Table 2), which reflect students' subjective evaluation of their learning experience. To avoid conflating perception with actual effectiveness, the main PBL Effectiveness Index reported in this paper is based on the objective rubric scores, while the questionnaire data are analyzed separately as supporting evidence of student perception.

To calculate the effectiveness index, it was calculated using formula 1.1 and the weighted score formula 1.2.

$$Effectiveness\ Index = \Sigma\left(\frac{weight}{100}\ x\ average\ score\right) \quad (1)$$

$$wighted\ score\ = \left(\frac{weight}{100}\right) x\ average\ score \quad (2)$$

The weight of each aspect was determined (e.g., cognitive and psychomotor aspects were weighted more heavily because they are the core of learning). The weight was multiplied by the average score to obtain the weighted score. All weighted scores were summed, and the result represented the PBL Effectiveness Index. The interpretation values were defined as follows: 1.0–1.9 =

Very Low (Ineffective); 2.0–2.9 = Low (Less Effective); 3.0–3.9 = Good (Effective); 4.0–5.0 = Very Good (Very Effective).

Results and Discussion

Results Project assessment rubric and effectiveness

After implementing Project-Based Learning (PBL) in an electrical engineering course, this study yielded several findings related to student learning outcomes and the quality of the non-invasive hemoglobin detection system prototype. This section presents the research findings obtained from the rubric assessment, student perception questionnaires, and observations and reflections during the learning process. The results of the PBL learning effectiveness matrix are shown in Table 3 and are also visualized in Figure 1.

Table 3. Results of Learning Effectiveness Evaluation

Roadmap Stage	Weight (%)	Average Score (1–5)	Weighted Score
Stage 1: Planning & Initial Understanding	20%	3.7	0.74
Stage 2: Technical Implementation	30%	3.4	1.02
Stage 3: Collaboration & Attitude	15%	4.1	0.62
Stage 4: Final Product & Validation	20%	3.2	0.64
Stage 5: Reflection, Presentation & Final Evaluation	15%	3.8	0.57
Total	100%	–	3.59

The effectiveness index of Project-Based Learning (PBL) was 3.59, which falls into the Good/Effective category. The strongest aspect was collaboration and attitude (soft skills), where students demonstrated high motivation and strong teamwork. The intermediate aspects included planning, technical implementation, and reflection, which were considered good but still required a deeper understanding of theoretical foundations and practical application.

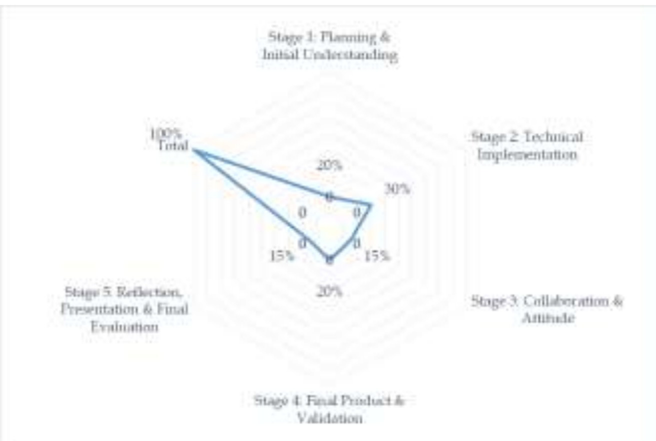

Figure 1. Distribution of effectiveness data

The weakest aspect identified in this study was the final product's measurement accuracy. Although the prototype functioned properly and was able to produce non-invasive hemoglobin estimates, its accuracy still fell below the expected standard based on comparison with reference values obtained from a hematology analyzer. Validation was conducted on 20 measurement samples collected from different participants. The device's predicted hemoglobin values were compared with laboratory results using standard statistical metrics, including Mean Absolute Error (MAE), precision, sensitivity, and specificity. The analysis showed an MAE of 0.75 g/dL and an overall precision level of 86 percent, indicating that while the system performed consistently, further algorithmic refinement and hardware calibration are required to reach clinical reliability. These findings confirm that the product is functionally viable but still needs iterative improvement to enhance measurement accuracy and robustness.

Questionnaire Results

This questionnaire was developed and distributed to 26 students participating in project-based learning (PBL) with a focus on developing a non-invasive hemoglobin level detection system. The purpose of this questionnaire was to measure students' perceptions of the learning experience through various aspects, including cognitive, psychomotor, affective, product, and reflection and satisfaction. The distribution of questionnaire results and data visualization in Figure 2 are shown in Table 4.

Table 4. Distribution of Questionnaire Results

Aspect	Average Score (1–5)	Interpretation	Notes
Cognitive (Knowledge & Understanding)	3.9	Good	Students understand the concept of hemoglobin & sensors, although there are still difficulties in data analysis.
Psychomotor (Technical Skills)	3.6	Good	Skills improved (assembly, troubleshooting), but still need more practice
Affective (Attitude, Motivation, Collaboration)	4.2	Very good	Students demonstrated high motivation, effective teamwork, and improved communication.
Products & Learning Outcomes	3.5	Good	The prototype is relevant and impressive, but accuracy is not yet optimal.
Reflection & Satisfaction	3.8	Good	Students are satisfied with PBL, hope this method is used more often

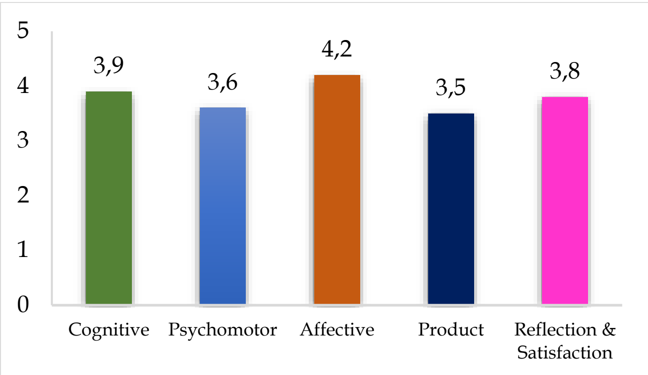

Figure 2. Data visualization

The questionnaire results showed that PBL had a positive impact on improving students' knowledge, skills, attitudes, and motivation. The affective aspect emerged as the main strength with the highest score, indicating an increase in learning motivation, cooperation, and team communication. Meanwhile, the product aspect was the weakest point, indicating that the quality of the prototype still requires further development. Overall, the total average score obtained was 3.8 in the Good/effective category, thus it can be concluded that the implementation of PBL successfully created a meaningful learning experience that was both relevant to real-world needs.

Results of Reflection and Observation

The results of reflection and observation obtained from a total of 26 students are shown in Table 5.

Table 5. Results of Reflection and Observation

Observed Aspects	Indicator	Observation Findings	Lecturer/Researcher Reflection
Class Participation & Discussion	Attendance, discussion involvement, initiative to ask questions	80% of students were actively present and involved in the discussion; some were still passively waiting for direction.	Students need to be encouraged to express ideas more often so that discussions are more even.
Teamwork	Division of tasks, collaboration, communication	The majority of groups were able to divide tasks well, although there were 2 groups whose contributions were less balanced.	A role rotation strategy is needed so that all members play an active role.
Technical Skills	Hardware assembly, coding, troubleshooting	Around 65% of students were able to assemble and conduct independent trials; the rest still relied on assistance from lecturers/assistants.	Additional practice sessions are needed to strengthen technical independence.
Motivation & Attitude	Enthusiasm, responsibility, punctuality	Students showed high motivation, despite some delays in completing the logbook.	Regular evaluation is needed so that progress can be more controlled.
Technical Constraints	Hardware, software, tool validation	Common problems: sensor connection errors, coding errors, and unstable tool accuracy.	Structured troubleshooting sessions and intensive guidance are required.
Student Reflection	Perception, satisfaction, learning gained	Students feel that PjBL adds real experience, improves teamwork, but realize that the product still needs improvement.	PjBL effectively enhances the learning experience even though it requires more time to perfect the product.

Student participation was high with good collaboration, several technical obstacles were encountered, and reflections showed increased motivation even though the product was not yet optimal. In this study, student perceptions were measured using a questionnaire, while external evaluations were obtained through observation and reflection sheets. Perception data and observation data were analyzed separately to avoid bias due to the different natures of self-report and external assessment. The PjBL Effectiveness Matrix in Table 6 and 7 summarizes the main aspects, indicators, and interpretation of the results based on these two types of data (Questionnaire; Observation & Reflection, N = 26), without averaging them into a single mixed score.

Table 6. PBL Effectiveness Matrix (Questionnaire vs Observation & Reflection, N = 26)

Main Aspect	Sub-Aspects / Indicators	Average Score (1–5) – Questionnaire	Interpretation (Perception)
Cognitive	Conceptual understanding, sensors, data analysis	3.9	Good – students understand the main concepts; data analysis still needs deeper study.
Psychomotor	Design, assembly, troubleshooting	3.6	Good – skills are improving; some students still depend on lecturer guidance.
Affective	Motivation, proactive attitude, collaboration	4.2	Very good – high motivation and positive collaborative attitude.
Product	Prototype quality, relevance, pride	3.5	Good – prototype is functional; measurement accuracy and robustness need improvement.
Reflection & Satisfaction	Satisfaction, critical thinking, evaluation	3.8	Good – students are satisfied, able to reflect, and wish PjBL to be used more often.

Table 7. PBL Effectiveness Matrix – Observation & Reflection (External Assessment, N = 26)

Main Aspect	Sub-Aspects / Indicators	Average Score (1–5) – Observation/Reflection	Interpretation (External Assessment)
Participation	Presence, discussion involvement, initiative	4.1	High – majority of students actively participate; a few remain passive.
Teamwork	Division of tasks, communication, contributions	3.8	Good – teamwork is generally effective, though some groups show unequal contributions.
Technical Skills	Independent practice and troubleshooting skills	3.5	Fair to good – students can work independently but still face technical issues.
Technical Constraints	Sensor issues, software errors, tool accuracy	3.3	Sufficient – technical obstacles are still noticeable; intensive guidance is needed.

In this study, perception data from the questionnaire and external assessment data from observation and reflection are deliberately analyzed and reported separately to avoid methodological bias; the questionnaire results show that students' perceptions of the PjBL implementation are generally in the good to very good range, with average scores of 3.9 for cognitive, 3.6 for psychomotor, 4.2 for affective, 3.5 for product, and 3.8 for reflection and satisfaction, indicating that students feel they understand the concepts, are developing technical skills, are highly motivated, and are satisfied with the learning experience, while the observation and reflection data indicate average scores of 4.1 for participation, 3.8 for teamwork, 3.5 for technical skills, and 3.3 for technical constraints, which describe how students actually behave and perform in terms of activity level, collaboration quality, independent practice, and the magnitude of technical obstacles; these two types of data are therefore not averaged into a single mixed score, but used in a complementary way, and the convergence of their interpretations (dominated by good to very good categories despite remaining technical constraints) strengthens the conclusion that the PjBL implementation is effective without overstating its impact.

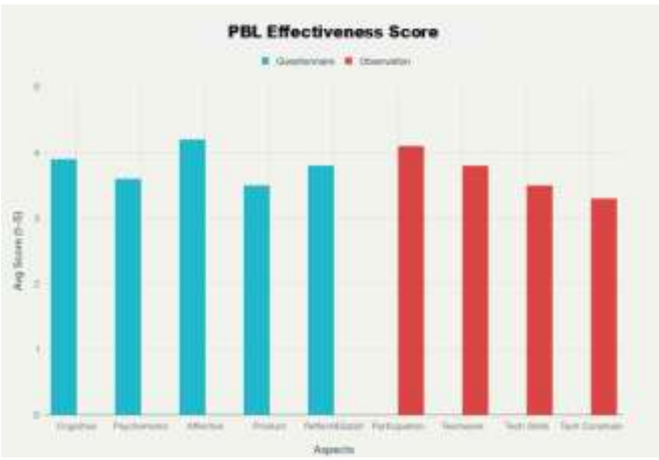

Figure 3. Results of distribution and effectiveness

Conclusion

Based on the overall rubric scores, questionnaire responses, and observation–reflection data, the implementation of Project-Based Learning (PBL) in this electrical engineering course can be concluded to be successful and educationally effective, even though the technical product still needs further refinement. The project assessment rubric produced a PBL effectiveness index of 3.59 on a 1–5 scale, which falls into the Good/Effective category and is supported by strong performance in collaboration and attitude, as well as satisfactory results in planning, technical implementation, and reflection. Questionnaire data with an overall mean of 3.8 in the Good/Effective range indicate positive student perceptions of gains in conceptual understanding, technical skills, motivation, and satisfaction, with the affective dimension emerging as a particular strength. Observation and reflection findings further corroborate these results, showing high participation rates, generally effective teamwork, gradually improving independence in technical tasks, and identifiable but manageable technical constraints. At the product level, validation of the non-invasive hemoglobin prototype against a hematology analyzer yielded an MAE of 0.75 g/dL and a precision of 86%, suggesting that the system is functionally viable and reasonably consistent, but still below clinical standards and therefore a candidate for iterative improvement in algorithm design and hardware calibration. Taken together, the convergence of rubric, perception, and observational evidence demonstrates that PBL effectively enhanced students' knowledge, skills, and attitudes and provided a meaningful, real-world–oriented learning experience, while simultaneously highlighting clear directions for future development of the prototype's measurement accuracy and students' technical autonomy.

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Author Contributions
S.W questionnaire, methodology and recap metrics; N.W writing journal, data processing; W.H methodology; A.R.H data processing; A.A data processing.

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Conflicts of Interest
There is no conflict in the making of this paper.

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