Integrating AI And Data Analytics In Assessing The Learning Effectiveness Of A PLC Training Model

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ABSTRACT

With the rapid advancement of industrial automation, Programmable Logic Controllers (PLCs) have become essential components in modern manufacturing systems. To enhance practical training in PLC programming, a hands–on experimental model based on the Mitsubishi FX5U PLC was developed. This study evaluates the effectiveness of the training model through student feedback collected via structured survey questions, incorporating both quantitative and qualitative measures. A Likert–scale rating system was utilized to assess key aspects such as conceptual understanding, programming proficiency, and practical applicability. Additionally, qualitative responses were analyzed using AI–driven sentiment analysis and data analytics techniques, including lexicon–based (VADER) and transformer–based (BERT) models. Word Cloud visualizations were employed to extract key insights from open–ended responses. The study offers a detailed evaluation of the PLC training model, identifying both its effective components and aspects requiring enhancement. By leveraging AI–driven evaluation techniques, the research demonstrates how data–informed insights can enhance instructional quality and inform future improvements in technical education.

KEYWORDS: Programmable Logic Controllers (PLCs), Mitsubishi FX5U, Hands–on training, Student feedback, Likert–scale, AI–driven sentiment analysis, VADER, BERT, Technical education.

1. Introduction

The rapid advancement of industrial automation has led to the widespread adoption of Programmable Logic Controllers (PLCs) as core components in modern manufacturing systems. These controllers play a crucial role in ensuring efficiency, flexibility, and reliability in industrial processes (Xu et al., 2018). With the emergence of Industry 4.0, there is an increasing demand for engineers proficient in PLC programming, system integration, and troubleshooting to meet the evolving needs of smart manufacturing (Monostori, 2014).

Despite the growing significance of PLC training, traditional educational approaches remain predominantly theoretical, often lacking sufficient hands–on practice. This gap in practical exposure limits students' ability to apply automation concepts effectively in real–world industrial settings (Barbosa et al., 2017). To address this issue, an experimental PLC training model based on the Mitsubishi FX5U was developed. This model enables students to interact with real PLC hardware, implement control algorithms, and troubleshoot automation systems in a structured, practical learning environment (Zhang et al., 2021).

A key innovation in this research is the integration of Artificial Intelligence (AI) and Data Analytics to evaluate the effectiveness of PLC training. Traditional assessment methods, such as manual grading and subjective surveys, often introduce bias and inconsistencies (Hinojo–Lucena et al., 2019). To enhance objectivity, this study employs a structured survey incorporating a Likert–scale rating system to quantify student perceptions of conceptual understanding, programming proficiency, and practical applicability. Additionally, AI–driven sentiment analysis analytics techniques–including lexicon–based (VADER) and transformer–based (BERT) models–are utilized to extract insights from qualitative responses. Word Cloud visualizations further support the identification of key themes in student feedback, enabling a comprehensive evaluation of training effectiveness.

By leveraging these AI–driven analytical methods, this study provides a data–driven assessment of PLC training effectiveness. The findings not only offer insights into student learning behaviors and knowledge retention but also highlight areas for improvement in PLC education. This research ultimately contributes to the modernization of automation training methodologies, ensuring that future engineers are well–equipped for the demands of Industry 4.0–driven manufacturing environments.Specifically, this study aims to evaluate the effectiveness of a revised PLC training model that integrates AI–based feedback analysis. It investigates whether such integration enhances the identification of pedagogical strengths and weaknesses, thereby improving the quality and relevance of automation education.

The subsequent sections of this paper are structured as follows: Section 2 presents the design and implementation of the experimental PLC Training Model, detailing its structure, features, and testing process. Section 3 focuses on the evaluation of the experimental PLC training model, utilizing Likert–scale analysis, Word Cloud visualization, and AI–based Natural Language

Processing (NLP) techniques to assess its effectiveness through student feedback. Finally, Section 4 provides a comprehensive conclusion, summarizing key findings and offering insights for future improvements in PLC training methodologies.

2. Experimental PLC Training Model

2.1. Structure and Features of the Training Model

To improve the effectiveness of PLC education, a custom–built experimental training model was developed based on the Mitsubishi FX5U PLC — a high–performance, industrial–grade controller widely used in modern automation systems (Mitsubishi Electric, 2022). The model was designed to address several limitations commonly found in traditional PLC training, such as prolonged setup time, frequent wiring errors, and inefficient troubleshooting processes, which remain significant obstacles in technical education (Ibrahim et al., 2021).

The initial design concept of the FX5U–based PLC training model, as illustrated in Figure 1, was developed in–house by the authors as part of a university–level research project at the Vietnam Aviation Academy. The model was tailored to meet instructional requirements in automation training and is not derived or adapted from any existing commercial or published platforms.

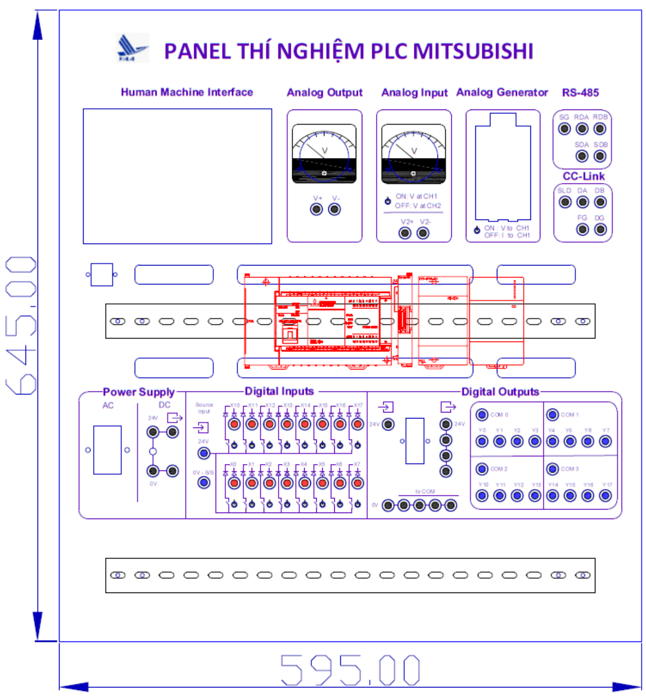

Figure 1: Initial design schematic of the FX5U-based PLC training model developed under an institutional project at the Vietnam Aviation Academy [see Acknowledgment]

The completed hardware configuration, shown in Figure 2, is organized around five key functional domains: (1) digital input/output control, (2) analog signal processing, (3) industrial communication, (4) instructional panel layout, and (5) HMI–based visualization and control. The model operates on a 220 V AC (alternating current) power supply, internally converted into suitable DC (direct current) voltages to safely power all components. At the core of the model is the Mitsubishi FX5U PLC, which offers highvspeed processing with a 1.2 ns instruction cycle — enabling real–time control capabilities essential in modern industrial applications (Hassan et al., 2023). Each of these functional domains is described in detail below, highlighting how the model supports hands–on training in industrial automation through realistic and structured instructional components.

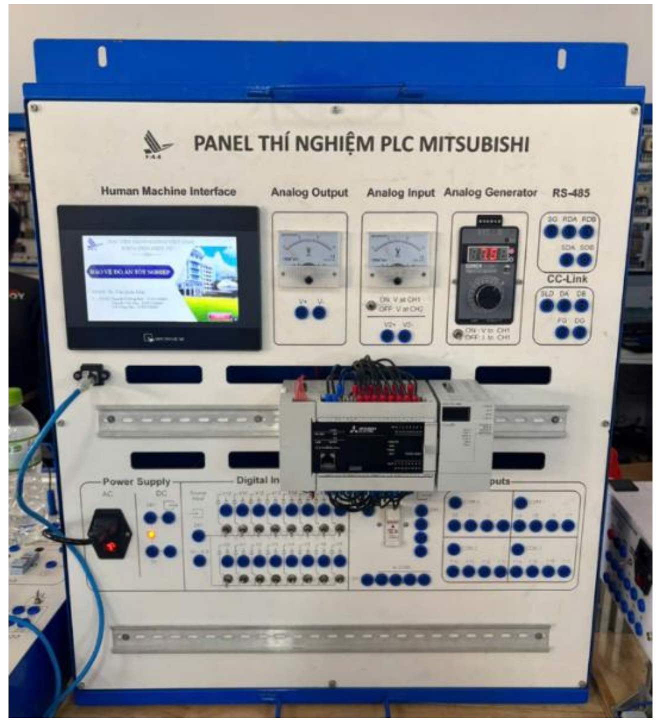

Figure 2: Physical implementation of the FX5U-based PLC training model with modular reconfiguration capability, developed under an institutional project at the Vietnam Aviation Academy [see Acknowledgment]

Digital Input and Output (I/O) Functionality: All digital I/O channels are accessible via standardized jack connectors mounted on the front panel. Input signals are simulated using pre–wired industrial toggle switches connected to selected input PLC's terminals, allowing students to replicate scenarios such as start/stop operations, safety interlocks, and sensor activation. Output channels are pre–connected to jack connectors linked to the PLC's output terminals. Students can mount relay modules onto the provided DIN rail and wire them accordingly to perform logic control experiments safely and flexibly.

Analog Input and Output Capabilities: The model includes two 12–bit A/D (Analog–to–Digital) input channels connected to a built–in analog signal generator capable of producing standard 0–10 V and 0–10 mA outputs. These signals simulate the behavior of real industrial sensors in process control. An analog dial gauge is integrated into the panel to allow real–time monitoring of input signal strength. On the output side, the FX5U's 12–bit D/A (Digital–to–Analog) channels generate analog control signals that are displayed via a digital voltmeter labeled "Analog Output" , allowing students to verify and analyze system responses (Chen et al., 2022).

Communication Interface: A pre–wired RS–485 serial communication port is included to support the Modbus RTU protocol. This feature enables students to gain practical experience with widely adopted industrial networking standards, including PLC–to–device communication, serial addressing, and data exchange with external sensors, SCADA platforms (Zhu et al., 2021).

Panel Layout and Usability: All components are permanently mounted on a structured training panel featuring clearly labeled terminals, standardized jack connectors, and a DIN rail for optional expansion. The panel is pre–wired to reduce manual setup time, minimize wiring errors, and enhance safety during lab sessions. This layout allows students to focus on PLC programming, control logic development, and troubleshooting, rather than complex hardware assembly (García & Fernández, 2020).

HMI–based Visualization and Control: To support real–time system monitoring and interaction, the model integrates a Weinview TK8071iP Human–Machine Interface (HMI), as shown in Figure 2. The HMI enables students to visualize process states, control variables, and execute automation logic interactively. This function not only enhances intuitive understanding of system behavior but also exposes students to industrial HMI usage. Furthermore, the modular architecture of the model supports flexible reconfiguration, allowing learners to design and test a variety of PLC control logic scenarios without extensive rewiring (Martínez et al., 2019).

By combining selected industrial–grade components with a clearly defined functional structure, the FX5U–based PLC training model provides a robust and versatile platform for developing both theoretical understanding and practical competencies in automation logic, analog interfacing, communication protocols, and human–machine interaction.

2.2. Model Model Testing and Observations

2.2.1 Challenges in the Traditional PLC Lab Setup

Before the new training model was introduced, students in PLC lab sessions worked mainly with individual PLC units and separate HMI panels. While this setup allowed for basic control exercises, it also came with several practical drawbacks. A major issue was the amount of time spent on physical setup –students had to wire sensors, actuators, and power connections manually. This often meant they spent more time connecting components than actually writing or testing programs (Barbosa et al., 2018).

Mistakes in wiring were also common. Misplaced wires or misunderstood diagrams sometimes caused the system to behave unpredictably or even led to hardware problems, which disrupted the learning process (Nguyen et al., 2020). These kinds of errors were especially frustrating for beginners who were just getting used to working with industrial equipment.

Another limitation was the lack of flexibility. Because the setup was fixed and not easily modified, students had fewer opportunities to try out more advanced or customized automation scenarios. Adjusting the system to fit new tasks usually took a lot of time and effort, which limited creativity and deeper exploration (Kim et al., 2021).

These difficulties highlighted the need for a more efficient and scalable system–one that would let students focus more on programming logic and troubleshooting rather than being bogged down by setup complexity.

2.2.2 Experimental Model Testing

To evaluate the operational stability and educational suitability of the FX5U–based PLC training model, a series of functional tests were conducted, focusing on power–up behavior, analog signal handling, and HMI–PLC communication. These evaluations were designed to ensure that the model not only meets instructional objectives but also reflects real–world industrial practices.

The first step involved a power–up and wiring inspection to verify safe operation under normal conditions. Upon supplying power to the system, the FX5U PLC and all integrated modules initialized correctly, with indicator lights confirming proper functionality. This confirmed that the electrical layout complied with basic industrial safety standards and was ready for instructional use.

Figure 3: Experimental setup for testing analog input/output signals, showing signal generators connected to the PLC analog modules

Following this, analog signal testing was conducted to assess the model's ability to process continuous I/O data. As shown in Figure 3, a built–in analog signal generator was used to simulate voltage (0–10 V) and current signals (4–20 mA), replicating the behavior of typical industrial sensors. These signals were processed through the PLC's A/D and D/A modules. The model demonstrated accurate signal conversion and stable analog data transmission. Although a signal generator was used for this initial validation, the input ports are fully compatible with real industrial sensors, allowing flexible adaptation to various training scenarios (Wang & Li, 2023).

To further validate system integration, HMI–PLC communication was tested using a Weinview TK8071iP HMI connected via Ethernet. As illustrated in Figure 4, the HMI successfully displayed real–time process data and responded to control inputs. Additionally, the system was able to detect and report simulated faults, allowing students to visualize system behavior and practice troubleshooting in real time. This functionality not only enhances students' understanding of industrial communication protocols but also reinforces their skills in fault diagnosis and interface design (Fernández et al., 2022).

Figure 4: HMI connected to the PLC via Ethernet, enabling real–time control and monitoring of system processes

In summary, the test results confirm that the FX5U–based training model is functionally robust, flexible in configuration, and pedagogically effective. It supports practical instruction in key areas such as PLC programming, analog signal interfacing, and integrated system control — making it a valuable tool for modern automation education.

3. Model Evaluation of the Experimental PLC Training Model

To evaluate the effectiveness of the Mitsubishi FX5U–based PLC training model, we conducted a structured survey using Google Forms. The survey was distributed to students who had recently completed the hands–on PLC training sessions, most of whom were in their second or third year and had previously studied PLC theory. Over the course of one month, we received 56 valid responses.

The main purpose of the survey was to identify the remaining challenges and limitations of the PLC training model, especially in terms of how well it supported students during practical sessions. By gathering direct feedback from learners, the study aimed to pinpoint specific difficulties they encountered, as well as areas where the model could be improved to better facilitate hands–on learning.

To ensure a well–rounded view of student experiences, the survey included both quantitative questions using Likert– scale and open–ended questions that allowed students to freely share their thoughts. All responses were anonymous and participation was entirely voluntary, in line with ethical standards for educational research.

3.1. Survey Structure and Key Areas of Evaluation

The survey was structured into four key sections, combining quantitative Likert–scale responses and qualitative feedback to support a comprehensive evaluation. The first section collected background information, including student demographics and self-assessed familiarity with PLC programming, providing a baseline for measuring learning progress. The second section focused on the perceived effectiveness of the training model, where students rated their experiences in areas such as conceptual understanding, programming proficiency, HMI usability, fault diagnosis, and real–world applicability. The third section addressed scientific and practical aspects, including usability, accessibility, instructional clarity, hands-on learning effectiveness, and the integration of software-based simulations with physical PLC modules. All items in the second and third sections were rated using a 5–point Likert–scale ranging from *"Strongly Disagree"* to *"Strongly Agree"* (Figure 5) to ensure consistent and meaningful interpretation of responses.

The final section gathered open-ended feedback, allowing students to express strengths, challenges, and suggestions for improvement. These qualitative responses were analyzed using natural language processing (NLP) techniques, including sentiment analysis and topic modeling, to extract key themes and trends.

3.2. Survey Results and Analysis

3.2.1. Likert–scale Analysis

For the initial survey analysis, we utilized Likert–scale analysis to evaluate students' perceptions of the PLC–based learning model. The Likert–scale is a well–established psychometric tool designed to quantify subjective opinions by capturing respondents' levels of agreement or disagreement with specific statements. This method enables us to systematically assess students' attitudes, measure response variability, and identify key areas for enhancement in the learning model

The box plot, as shown in Figure 5, illustrates the distribution of students' evaluation scores across various aspects of the PLC–based learning model. The majority of ratings range from 3 to 5, signifying a generally positive reception. The median scores for most criteria are clustered around 4 and 5, indicating that students largely perceived the model as beneficial in improving their conceptual understanding and practical skills.

Certain criteria display noticeable outliers, particularly in the lower range (scores of 1 or 2), suggesting that while most students evaluated the model favorably, a minority had significantly different experiences. Notably, the criterion related to troubleshooting PLC errors exhibits the highest variability, with scores spanning the entire scale from 1 to 5, indicating differing levels of perceived difficulty or effectiveness.

Key strengths of the model include aspects such as "The model helps me understand the principles of PLC operation" and "The combination of simulation and practice helps me learn faster." These criteria exhibit high median scores and low variability, suggesting that integrating theoretical knowledge with practical exercises is especially effective in enhancing student learning.

However, certain aspects may require improvement, as indicated by criteria with lower whiskers and more dispersed ratings. For instance, if "The model's HMI is intuitive and easy to use" received more varied responses, it may highlight the need for

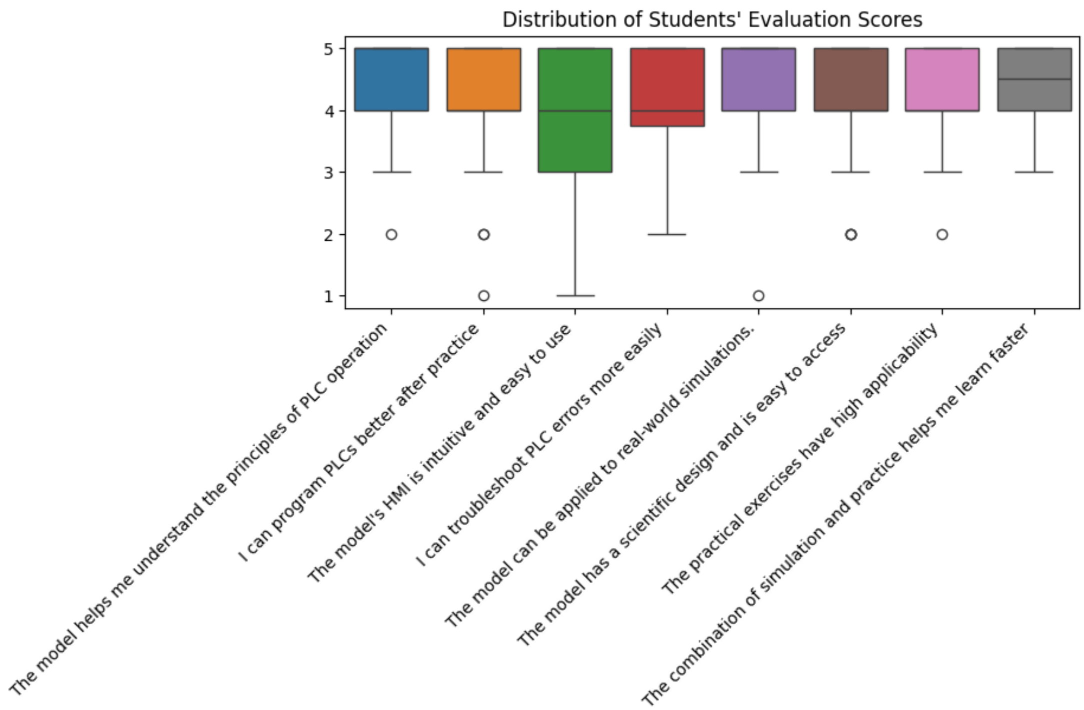

Figure 5: Distribution of survey responses using a 5–point Likert–scale ranging from "Strongly Disagree" to "Strongly Agree”

refinements in the user interface to improve accessibility and usability

Overall, the evaluation scores demonstrate that the PLC–based learning model is well–received, with consistently high ratings across most aspects. Nevertheless, the presence of outliers underscores the necessity of further refinements to address specific concerns and enhance the overall learning experience. Future studies should aim to investigate the reasons behind lower ratings and implement targeted improvements to optimize the model's effectiveness for a broader range of students.

3.3.2. Natural Language Processing Analysis

As mentioned earlier, the final section of the survey collected open–ended feedback, allowing students to highlight strengths, challenges, and provide suggestions for improvement. These qualitative responses were analyzed using NLP techniques, such as sentiment analysis and topic modeling, to identify recurring themes and sentiment trends.

a) Word Cloud Analysis

Figure 6 presents the first Word Cloud, which highlights the standout advantages of the training model based on students' feedback. In this visualization, the size of each word corresponds to its frequency, making it easier to identify key themes. Prominent terms such as *"easy"*, *"use"*, *"students"*, *"practice"*, and *"understand"* appear in larger font sizes, suggesting that learners find the model user–friendly, accessible, and effective for hands–on learning. Additionally, the presence of terms like *"PLC"*, *"SCADA"*, and *"communication"* underscores the model's relevance to real–world industrial applications. Overall, these results indicate that students appreciate the model's practicality and clarity, though further refinements may enhance the user experience.

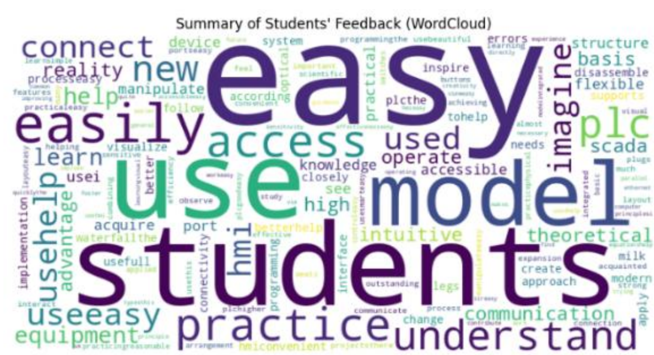

Figure 6: Word Cloud highlighting key advantages of the PLC training model as perceived by survey participants

In contrast, a second Word Cloud focusing on challenges encountered during practice (Figure 7), highlights terms such as *"model", "HMI", "wire",* and *"students"*, which suggest a strong focus on the system's hardware and interface. However, terms such as "*difficult*", *"sometimes", "problems",* and *"cumbersome"* indicate that students encountered challenges, particularly related to connection setup, wiring complexity, and overall system usability. The presence of *"new"* and *"practice"* suggests that students are still adapting to the system but acknowledge its learning potential. While the model is valuable for hands–on learning, addressing usability issues–especially related to HMI and wiring–could improve the learning experience.

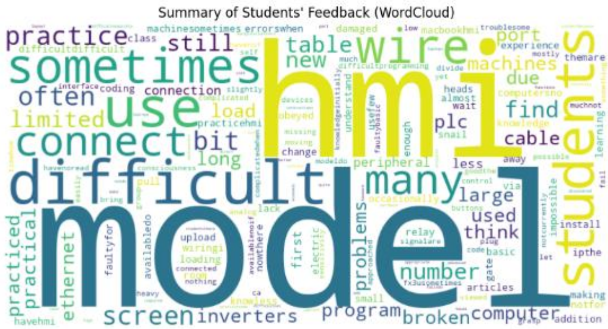

Figure 7: Word Cloud of difficulties encountered during practice Word Cloud illustrating common difficulties encountered by participants during hands–on practice with the PLC training mode

Lastly, as shown in Figure 8, words like *"sensor," "traffic,"* and *"school"* suggest the model's practical applications in automation and control systems. Terms such as *"improve," "check,"* and *"change"* indicate areas where students see potential for refinement, likely in equipment reliability, system functionality, or usability. The presence of *"recommend"* suggests that, despite some issues, students recognize the model's value. Enhancing equipment quality, system stability, and usability could further strengthen its effectiveness in educational settings

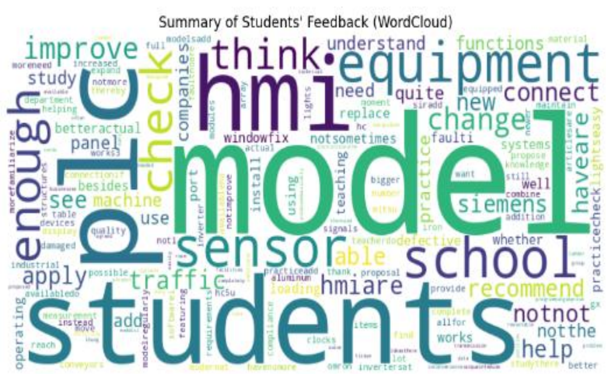

Figure 8: Word Cloud summarizing participants' suggestions for improving the PLC training mode

While Word Clouds are useful for identifying frequently mentioned words and key themes in textual data, they have several limitations. One major drawback is that they do not provide context–Word Clouds display words in isolation, without indicating whether they were mentioned in a positive, negative, or neutral context. For example, a word like *"difficult"* may appear prominently, but without further analysis, it is unclear whether students are describing a necessary challenge that aids learning or a frustrating obstacle that hinders progress.

Additionally, Word Clouds do not capture sentiment or the relationships between words. This means they cannot determine whether students expressed satisfaction, frustration, or mixedopinions about specific aspects of the model. To address this limitation,

AI–based NLP techniques such as Sentiment Analysis are employed. These methods analyze text at a deeper level, detecting emotions, attitudes, and polarity (positive, negative, or neutral sentiment) within student feedback. By applying sentiment analysis, we can gain a more nuanced understanding of how students perceive the learning model and pinpoint areas that require improvement beyond just word frequency.

b) AI–based NLP Sentiment Analysis

To analyze students' feedback, two AI–based NLP models were utilized: VADER (Valence Aware Dictionary and sEntiment Reasoner) and BERT (Bidirectional Encoder Representations from Transformers).

VADER is a lexicon–based model designed for sentiment analysis in short texts, assigning sentiment scores based on predefined word valence. It performs well on structured feedback but struggles with context–dependent meanings. In contrast, BERT, a deep learning–based transformer model, captures context and nuance, effectively handling sentiment shifts, irony, and complex expressions. However, it requires more computational power and is less interpretable. The comparative overview between BERT and VADER can be found in Table 1.

Table 1: Comparative overview of VADER and BERT sentiment analysis approaches

Feature	VADER	BERT
Model Type	Lexicon–based, rule–driven	Transformer–based, deep learning
Context Awareness	Limited (word–level)	High (contextual embeddings)
Sentiment Score Range	–1 to 1	–1 to 1
Neutral Sentiment Handling	More likely to classify as neutral	Distinguishes subtle sentiment shifts
Performance on Short Texts	Effective	Effective
Performance on Complex Sentences	Limited	Strong
Interpretability	High (transparent rules)	Lower (black–box nature)
Computational Requirements	Low	High

Figure 9 illustrates the distribution of sentiment across three categories of student feedback: standout advantages of the model, difficulties encountered during practical sessions, and suggestions for improvement.

Within the standout advantages category, the VADER algorithm identifies a moderate concentration of positive sentiment (ranging from 0.4 to 0.8), whereas the BERT model reveals a more pronounced cluster in the high–positive range (0.75 to 1.0). This suggests not only general approval but also a strong level of student satisfaction with the training model. These results are reflected in representative comments such as: *"Yes, I find it new and easy to use for students new to PLC"* and *"Helps students visualize and understand how PLC works, inspiring students to program"*.

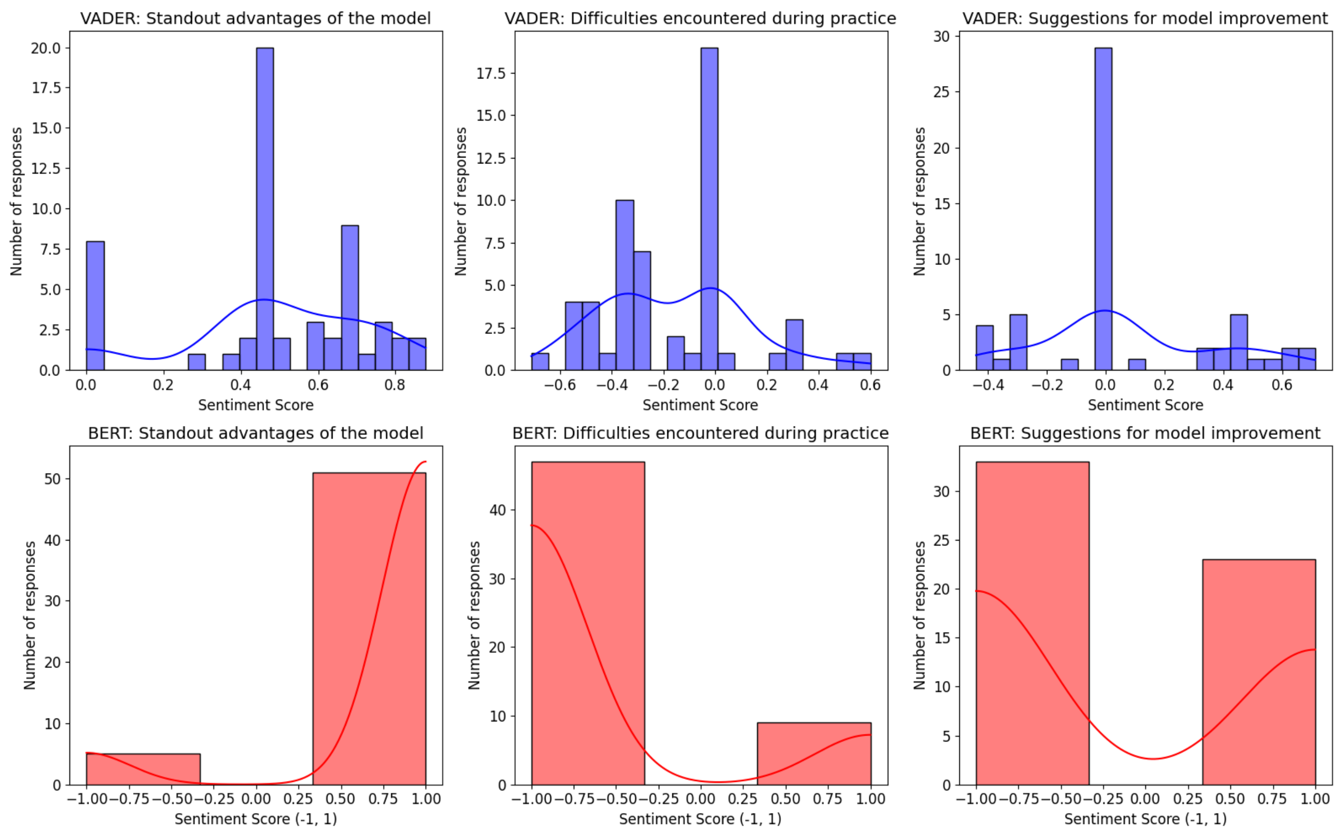

Figure 9: Word Cloud highlighting key advantages of the PLC training model as perceived by survey participants *AI–based NLP sentiment analysis integrating BERT and VADER for user feedback interpretation*

In difficulties encountered, VADER displayed scattered sentiment scores near neutral, making it difficult to isolate specific pain points. BERT, however, pinpointed a negative sentiment concentration in the -1.0 to -0.5 range. This corresponds to feedback like: "Sometimes the HMI screens still fail to load and crash" and "Sometimes I can't connect to the computer. The number of models is limited, so should divide into large groups to practice, so many people can't practice proficiently". These quotes support BERT's capability to extract clearly defined concerns related to technical usability

When analyzing suggestions for improvement, VADER mostly yielded neutral outputs, often overlooking the tone and intent behind students' words. In contrast, BERT revealed a bimodal sentiment distribution, capturing both negative and constructive suggestions. This is evidenced by statements such as *"Upgrade to larger HMI, change model material instead of iron, aluminum for more flexible movement"* (negative sentiment) and *"I hope to be able to combine with other models in the department, such as inverter and measurement models. Thereby helping you to apply more models, improving the quality of the subject requirements"* (positive suggestion). This dual–polarity underscores the constructive nature of student feedback.

Overall, the sentiment analysis demonstrates that students appreciate the hands–on effectiveness of the PLC training model but also experience usability issues – particularly in HMI configuration, wiring, and system connectivity. While VADER offers a high–level overview, BERT's contextual sensitivity enables more granular and interpretable insights. The integration of representative student quotes further validates the sentiment analysis results and highlights areas for system improvement. These findings suggest the need for refining technical documentation and interface design to enhance the overall learning experience.

4. Conclusions

This study evaluates the effectiveness of the PLC training model through student feedback using both quantitative and qualitative methods. Likert–scale results indicate high satisfaction, especially in conceptual understanding, programming skills, and practical application. However, this method has limitations, such as its inability to capture nuanced opinions and potential response bias.

The Word Cloud analysis revealed key thematic patterns in student feedback, underscoring strengths such as ease of use and practical applicability, alongside recurrent concerns related to hardware connectivity and system usability. However, Word Cloud lacks contextual understanding and cannot differentiate between positive and negative sentiments. To address these limitations, AI–based sentiment analysis was applied, with VADER effectively detecting sentiment polarity and BERT providing deeper contextual insights. The comparison suggests that transformer–based models offer more accurate and detailed sentiment classification.

Overall, this study demonstrates the value of AI–driven evaluation techniques in educational research. Integrating sentiment analysis and word frequency visualization provides a more comprehensive understanding of student experiences, guiding improvements in PLC training. Future research should explore adaptive learning solutions and further refine the experimental model to enhance teaching effectiveness

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