

Article

The Establishment and Evaluation Model of the Thematic Deep-Learning Teaching Module

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Abstract: In recent years, the application of artificial intelligence (AI) in industry has matured, requiring deeper learning and integration of existing technologies. This study started with technical education to improve the professional quality of human resources. The double-triangular fuzzy number and gray area testing methods in the fuzzy Delphi method (FDM) were used to evaluate expert consensus, plan technical capability indicators, and ensure the integrity and appropriateness of teaching materials. Based on these indicators, special subject teaching course units were designed and integrated into existing courses for experimental teaching and evaluation. The teaching module arrangement in this research used a virtual instrument control system with LabVIEW v2021 as the GUI and the myRIO controller. The proposed system integrates an artificial neural network (ANN) AI model built with Python v3.7 for data analysis and prediction, forming an embedded teaching module for a deep learning-oriented intelligent robotic environmental monitoring system. This study evaluated students' acceptance of deep learning robotics teaching modules and their impact on improving their technical skills. The psychomotor scale established by the scholars was adopted and revised, including this study's technical ability indicators. The test-retest reliability of the psychomotor scale was high. The results revealed that the post-test scores of the psychomotor scale were significantly better than those of the pre-test, indicating that students' overall technical abilities improved. Students' affective attitudes toward the four dimensions of teaching material and equipment, cognitive development, skills performance, and self-exploration were positive. Feedback revealed that students who participated in the teaching experiment responded positively on all levels of the affective scale, indicating increased motivation and willingness to continue learning. This study successfully constructed a teaching module and evaluation model for deep learning robotic environmental sensing and control. The teaching module and evaluation model established through this research contribute to the cultivation and effectiveness evaluation of relevant technical talents.

Keywords: deep learning; teaching module; teaching evaluation; themed teaching; FDM



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1. Introduction

In this new era of technology, companies and developers worldwide are focusing on artificial intelligence (AI), machine learning (ML), and deep learning (DL). AI empowers machines to think independently and make judgments without human intervention. Taiwan's robotics industry has also been advancing rapidly, with AI-based robots poised to become a trillion-dollar industry. Smart robots powered by AI technology integrate a range of advanced technologies, including the Internet of Things (IoT), big data, ML, DL,

neural networks (NNs), and expert systems [1]. These robots significantly enhance human work efficiency, improve quality of life, and hold immense development potential. The convergence of AI and the IoT has resulted in the increasingly complex architecture of the Internet of Everything (IoE). The vast amounts of data generated by IoT devices drive continuous improvements in machine learning and deep learning technologies, fostering the creation of sophisticated algorithms and intelligent AI-powered robots [2].

DL is an artificial intelligence technology inspired by how the human brain filters information, primarily by learning from examples [3]. It helps computer models predict and classify messages by filtering large amounts of input data. DL processes information in a similar manner to the human brain; thus, it can be defined as a neural network architecture containing a large number of parameters and multiple layers [4–7]. Therefore, it can take advantage of system intelligence and be widely used in existing industries.

DL is the most advanced technology in the industry, and VI and control technologies are in high demand. Integrating the two technologies into teaching will provide technical and vocational schools with the ability to integrate industrial technology needs into VI and control technology courses. Moreover, the integration of research, development, and innovation in teaching provides students with opportunities to take technical courses oriented to industrial practice. To address the improvement of industrial skills and robot development technology teaching, this research fully exploits the advantages of virtual instrument-controlled automatic measurement systems [8] and proposes the application of DL in embedded teaching modules on the subject of robotic environmental monitoring technology. The construction and evaluation model uses DL technology to develop the robot's environmental monitoring system and control the robot's various sensing and control functions and other automatic measurement technologies to provide technical and vocational school teaching in robot design and practical technology courses. To evaluate teaching effectiveness, research has focused on applying emerging robotic environmental monitoring technology to teaching aids and equipment systems (physical or computer simulation) of robot education, ensuring a teaching approach that combines industrial needs and R&D innovation.

Regarding industrial demand, intelligent robots are also widely used in production and services. To keep pace with the continuous improvement of AI technology and technological innovation in the industry, enhancing the professional quality of human resources must start with technical education. This research provides embedded teaching materials and teaching aids on the subject of environmental monitoring technology for DL-oriented robots in line with Taiwan's technical and vocational education and integrates them into courses related to robot design and practice so that students can continue skills and equipment learning for industrial careers. Thus, the application technology of Taiwan's intelligent robots can be simultaneously improved to meet social needs, allowing economic growth and academic development.

The motivation for this research has two main aspects. First, from an industrial perspective, it encompasses (1) the continuous advancement of AI technology in the industry, which requires corresponding improvements in professional skills; (2) the increasing value of the application of intelligent robot technology; and (3) the demand for industry talent. Second, from an educational perspective, it involves (1) the need for AI robot teaching materials and equipment that align with Taiwan's technical education; (2) the requirement for skills and equipment learning that can be extended to the industry; (3) alignment with the current situation of technical and vocational education in Taiwan (including national industrial technology and art competitions and world skills competitions); and (4) the training needs of current technical teachers (such as training for professional teachers in technical and vocational education).

Given the above research motivations, a DL-oriented intelligent environmental monitoring technology-embedded teaching module is constructed, and an evaluation model is proposed. It is hoped that this will be considered in the construction of teaching materials and teaching aids and in teaching arrangement planning to meet the needs of various research motivations. This research focuses on the DL aspect of AI intelligent robot technology, which has not yet been promoted in robotics education; plans a theme-based DL-oriented robot teaching module; and integrates it into a curriculum using a theme-based teaching method. Students are expected to incorporate the concept of DL when learning thematic robot design and practice using advanced AI robots. The research content includes constructing in-depth learning-oriented thematic teaching module teaching materials, teaching aids, and teaching experiments and evaluating learning effectiveness. In terms of teaching subjects and experimental teaching, this research plan targets students in electrical or electromechanical-related fields at the undergraduate level in technical colleges as the research subjects for experimental evaluation.

This study combines the Laboratory Virtual Instrument Engineering Workbench (LabVIEW) and myRIO for the “Robot Design and Practice” course to conduct thematic learning and teaching evaluation in the IoT. IoT technology can be integrated into the robot course, allowing the incorporation of big data collection technology into the system and enabling more advanced AI technology to be integrated into the learning system module. This interdisciplinary research on AI and robotics education aims to develop more advanced practical teaching materials for intelligent robots. Constructing and evaluating a DL-oriented thematic teaching module for robotic environmental monitoring technology will enable students to integrate artificial intelligence and educational robots more deeply into relevant robot design and practice courses.

The primary purpose of this study was to design and plan a set of teaching modules for robotic environmental monitoring systems that apply DL and are suitable for industrial talent cultivation in technical colleges and universities and to allow students to learn about robots in depth by embedding themes into subject teaching. Regarding technology and the ability to integrate environmental monitoring systems and construction, we can move toward high-end AI technology. Its related technical concepts include DL of AI, integration of sensing devices, IoT communication technology, big data, and practical teaching aids. Module configuration, programming, a servo host controller, etc., were also included so that students can enter the industry in the future with the ability to integrate DL technology into robot design, environment monitoring technology, and practice. This research also set up the teaching module. After completion, experimental teaching was conducted to evaluate the effectiveness of this thematic teaching.

2. Preliminaries

Competency indicators translate students’ abilities, skills, or attitudes into measurable data to track and assess their learning progress. Breaking down general indicators into more specific ones improves the evaluation of each learning objective. This study aimed to develop technical competency indicators for a teaching module focused on deep learning and robot-based environmental monitoring systems. The study draws on the technical competencies outlined by Yao et al. [9,10], incorporating and adapting them to suit the course on deep learning robot design and implementation and producing a tailored set of technical competency indicators. A five-point Likert scale was used, and 15 experts were invited to participate in discussions and provide feedback through questionnaires. After the questionnaires were collected, the fuzzy Delphi method (FDM) was used, and triangular fuzzy numbers were used for defuzzification.

Virtual instrument (VI) technology mainly uses NI's LabVIEW v2021 software. LabVIEW is a module for industrial AI calculations that gradually enhances the software's ability to directly perform AI calculations. This research uses VI technology and LabVIEW software to construct and develop a theme-based teaching module for robotic environmental monitoring systems oriented toward DL. Through VI, the software, which is defined based on user requirements, will define the functions of general measurement and control hardware. VI integrates mainstream commercial technologies into flexible software and various measurement and control hardware, enabling engineers and scientists to establish user-defined systems that fully meet application needs. There are many research applications, such as measurement and control system program simulation of ML algorithms [11], building structure monitoring [12], measuring the temperature distribution of simulated underground power line models, and identifying the characteristics of the thermistors used. Other applications include the calibration of each measurement channel and temperature verification measurements [13], high-speed equivalent time sampling (ETS) [14], transmitter electrical system test technology [15], promoting the embodiment of the musical instrument learning environment and the effect of visual cues in virtual reality [16], GPU-accelerated virtual instruments for polarization resonance soft X-ray scattering [17], thermoelectric energy generation and optimization of material parameters in the process [18], application course teaching reform based on the OBE concept [19], real-time environment monitoring [20], robotic systems [21], production line electronic circuit measurement, and embedded innovative system applications [22]. With VI, engineers and scientists can reduce development time, design higher-quality products, and lower design costs. This study used the NI myRIO embedded system as the robot system controller. The system connects to myRIO as the control host through wireless transmission. Embedded system methods were used to achieve the program computing capabilities and sensing control capabilities required by the system. Python v3.7 was used to develop AI modules and integrate them with LabVIEW to build a deep-learning virtual instrument control system.

3. Methods

3.1. Methodology

This study first collected and organized the relevant literature on intelligent robot technology in the industry to achieve the research objectives. It planned to use LabVIEW combined with myRIO and programming in Python to develop and test a DL-oriented intelligent environmental monitoring system. Then, we focused on the learning background, content, practical equipment, and unit organization required to teach a DL-based robot intelligence teaching module. Then, material writing, integration, and planning were conducted to design core course units for DL technology in a thematic DL course. Furthermore, it formulated the technical competence indicators and DL content in a robot intelligence environmental monitoring system course, allowing students to integrate their learning of DL concepts and the practical operation of robot intelligence technology with cognitive and skill aspects when studying robot design and related courses or themes, thus completing the construction of the teaching materials and teaching modules.

To improve the correspondence of teaching materials and teaching aids and the accuracy of skills assessment, a study on the correspondence capability indicators of teaching aids and materials was conducted to complete the construction of a DL-oriented robot thematic teaching module and establish skill and affective scales as the basis for teaching experiment evaluation.

To ensure the completeness and appropriateness of the teaching materials, the writing of the materials was reviewed by experts for suitability, followed by experimental teaching

and evaluation. Through thematic embedded teaching, the DL-oriented robotic environmental monitoring system thematic teaching module was integrated into the planned curriculum, and evaluation and revisions were conducted after teaching. This study adopted experimental research methods and combined them with scaling survey methods to explore students' acceptance of this DL-oriented robotic environmental monitoring system thematic teaching module and its impact on the improvement of professional technical capabilities.

This study's research methods include literature analysis, expert consultation, interviews, double triangle fuzzy numbers, and gray zone test methods of the FDM, as well as experimental research methods such as quasi-experimental design, teaching evaluation, etc. The following introduces the methods and steps of this research, as shown in Figure 1.

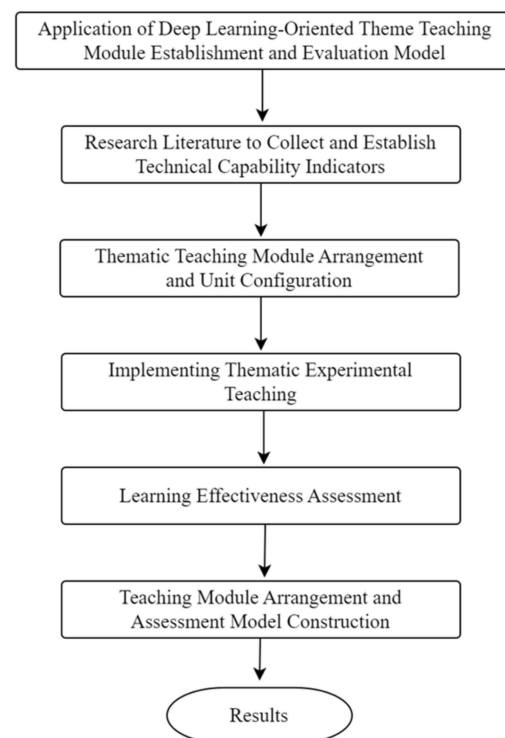


Figure 1. Research framework flowchart.

3.2. Technical Ability Indicators and Curriculum Planning

This study discusses the relevant information on the thematic teaching module of the robotic environmental monitoring system based on DL through literature collection and analysis, and it refers to the technical capabilities established by Yao et al. [10] in "Evaluating Thematic Approach Teaching of Robot Design and Practice Course Through Psychomotor and Affective Domains" indicators. In this study, 4 domains and 21 indicators of its capability indicators were used, and they were summarized into a questionnaire to determine the feasibility, spread, and comprehensiveness of the capability indicator items and technology construction direction of the first draft of the questionnaire. To determine the appropriateness, relevant experts and scholars were invited to form the FDM questionnaire group to provide opinions.

This study adopted FDM technology, utilizing the concepts of the Delphi method for questionnaire design, and used the three-point estimation method plus the method of experts directly defining membership functions. The FDM, modified from the Delphi method, can consider relatively complete information acquisition while solving semantic ambiguity problems. The Delphi method steps designed with this concept were expected to have better consensus convergence.

When considering the minimum acceptable sample for a homogeneous panel of experts, good results can be obtained with a panel of 10–15 people [23,24]. Therefore, this study, through a literature review and analysis and taking into account the time for expert opinions and the exchange of multiple opinions, invited 15 experts to participate in discussions and answer the questionnaire. The questionnaire used a five-point Likert scale and was distributed via email. A single-round questionnaire survey assessed the importance of expert reviews and provided qualitative and quantitative professional advice. After conducting the FDM survey, triangular fuzzy numbers were used for defuzzification. The gray zone test method, screening, and selection of appropriate evaluation indicators followed. The opinions on the competence indicators of the teaching modules in one round of the FDM were compiled and revised to ensure the questionnaire's validity and clarify the meaning of the teaching topic discussed in this study.

3.3. *Planing Thematic Teaching Courses and Unit Configuration*

This study uses the practical requirements of industrial technology to develop a themed teaching module on DL-oriented robotic environmental monitoring systems. It focuses on selecting and planning teaching materials and tools, designing curriculum units, and correlating capability indicators with teaching content. The teaching module combines LabVIEW and myRIO using Python programming and integrates IoT technology into the robot course. This allows big data collection technology to be integrated into the system, enabling higher-level AI technology to be incorporated into the learning system module. This interdisciplinary research in AI and robotics education aimed to develop more advanced practical teaching materials for intelligent robots. Constructing and evaluating themed teaching modules on DL-oriented robotic environmental monitoring technology will enable students to deeply integrate AI and educational robots into related courses on robot design and practice.

3.3.1. Capability Indicators of DL Robotic Environmental Monitoring System

Capability indicators transform the abilities, talents, or attitudes students should possess into observable and assessable specific data to indicate, display, or reflect students' learning performance. To accurately grasp each learning objective, it is advisable to break down the concept of capability indicators into detailed capability indicators. This study adopted the capability indicators established by Yao et al. [9] in "Establishment of Capability Indicators for Robot Design and Practice", which was based on the myRIO embedded system introduced by NI Corporation, and established capability indicators for introducing myRIO into robot design and practice courses.

This text discusses using the FDM to gather feedback from experts in robotics technology and assess the appropriateness and importance of the constructed capability indicators and technical aspects. The aim was to ensure the accuracy and professionalism of the indicators and develop a theme-based teaching module for the technical capabilities of a DL-oriented robotic environmental monitoring system. This process was also used to plan the curriculum and serve as the primary assessment basis for technical evaluation, ensuring that the skills assessment during experimental teaching aligns closely with the teaching objectives and effectively captures student skill development.

3.3.2. Course Planning for DL in Robotic Environmental Monitoring Systems

This study focuses on the practical implementation of DL-themed IoT smart home robot systems. The main teaching objective is to build a home appliance control cruising robot through remote monitoring. The course planning adopted the Spiral-ADDIE&R Model [9]: Analysis, Design, Development, Implementation, Evaluation, Examination, and Revising, along with other course planning designs, developments, and theories. This was

used to plan the course, establish capability indicators, and devise teaching content, as well as to develop methods for improving teaching materials and tools in the future.

In terms of software, it used the user-friendly design interface of LabVIEW. For hardware, it adopted the myRIO controller, which can control the switches of household appliances using network relays. In the event of an occurrence, it can notify users through the LINE app on their mobile phones. The robot is equipped with environmental data perception, such as temperature, humidity, light intensity, and vibration. An image recognition system integrated into the robot detects moving objects and can serve as a security alert system. Building on this design, a LabVIEW-based IoT device robot system has been developed, featuring autonomous patrolling, home appliance control, image recognition analysis, LINE notifications, home environment sensing, and wireless remote control. This system serves as a teaching aid for cultivating talent in robotics.

This teaching material aims to create a smart home more simply by using myRIO to control network relays to manage household appliances. myRio utilizes robot mobility to provide sensors, allowing for home patrolling with programming and eliminating the need to install sensors in various corners of the home. It also provides image recognition for home security, achieving a smart home environment. In the event of occurrences, it notifies users through the LINE app on their mobile phones. The teaching objectives of this material are (1) learning the construction and control of myRIO wheeled robots with autonomous cruising functionality; (2) learning the design of robot monitoring; and (3) learning the integration of environmental sensing and network relays to implement IoT technology.

To achieve the objectives of the teaching material, this paper is based on a literature review. First, the relevant technical literature on mobile robots, AI, smart home technology, and image recognition was collected to obtain data on the architecture of smart home systems and the construction of mobile robots. Then, a hardware development platform for mobile robots was selected, and a robot prototype was built using hardware structure and 3D printing. Through the LabVIEW software, a simulated smart home monitoring system was created, covering temperature, humidity, light intensity, vibration, gripper, and recognition. This integrated sensor data and the control of network relays, along with the addition of a LINE notification system. After repeated testing and system structure improvement, a LabVIEW-based IoT and environmental monitoring equipment was completed.

3.4. Planning and Establishment of Teaching Modules

Planning the Software for the Themed Teaching Module: This study utilized virtual instrument technology and LabVIEW software, in conjunction with a host server, myRIO controller, and robotic devices, to develop different control software for mobile control systems and sensor data monitoring in DL systems. LabVIEW software was chosen as the graphical user interface (GUI) for intelligent robotic human-machine monitoring. Python was also used to construct an embedded artificial neural network (ANN) AI model within LabVIEW for data analysis and prediction. Additionally, LabVIEW was responsible for sensor data acquisition, including temperature, illumination, humidity, and indoor personnel, achieved through NI DAQ (National Instruments Data Acquisition) devices for control functionality.

Integrating LabVIEW programming to construct an intelligent environmental monitoring system that integrates DL modules represents the most advanced technology in the industry and practical skills in robot design. This integration will allow vocational schools to offer courses in robot design and practical monitoring technology, enabling them to incorporate industry needs and innovation into their teaching content and allowing students to study industry-oriented practical courses.

Planning the Hardware for the Themed Teaching Module: To establish the hardware design and physical structure required for the robot's mobile control system and sensor data monitoring using DL technology, the industry- and mainstream technology-oriented myRIO controller was utilized. The myRIO controller controls devices through network relays and provides mobility for sensors through robot movement. Additionally, it is used in conjunction with programming to analyze paths, predict movement directions, and control automatic cruise functions. The myRIO controller is capable of monitoring data collection for robot carrier movement; it selects the Parallax infrared distance sensing module and then uses Python to create a path prediction AI module.

Planning of Educational Tool System for Sensor Control Technology in DL: This research utilized LabVIEW with the myRIO controller and Python programming to construct an embedded ANN AI model for data analysis and prediction and implement the data and computational algorithms required for DL technology. In conjunction with the host server and myRIO controller, a themed educational module for DL robots was established for robot mobile control systems and sensor data monitoring. The educational tools and materials developed can be used in themed robot technology units or DL technology units for relevant technical courses.

Robot System Integration and Testing: The integration of software and hardware equipment for the themed teaching module on intelligent DL robots was established to ensure the planning and physical structure of the mobile control system and sensor data monitoring in the themed teaching module. This involved developing robot system integration testing through programming language writing and IoT technology. The creation of teaching implementation tools was carried out, and following successful integration, the research report was written. If issues arose with the system, returning to the experimental steps was necessary to identify the problem.

3.5. Teaching Assessment Scale, Experimental Teaching Planning, and Evaluation Strategies

The research planned to develop a teaching assessment scale for conducting teaching experiments, including psychomotor and affective aspects. A scale was created for the psychomotor and affective dimensions, and the psychomotor scale developed by Yao et al. [10] was adopted, incorporating considerations of technical competence indicators, including hardware construction and software–hardware system integration. The original Kendall concordance coefficient test yielded a Kendall's W coefficient of 0.885 and a chi-square value of 99.232, with a significant p -value of 0.000, which is less than 0.05. For the psychomotor scale of themed learning effectiveness, a questionnaire developed by Yao et al. [10] was modified, with an original reliability test showing a Cronbach's α of 0.928. Expert validity testing was conducted on the scale, and its reliability was evaluated using KR20, Kendall's concordance coefficient, and Cronbach's α .

This study used the theme-embedded teaching strategy in the technical core course to conduct experimental teaching of the DL-oriented robotic environmental monitoring-themed teaching unit. It is planned that the "Automatic Measurement Technology" course will be opened in the third-year electrical unit of a national university. It is scheduled from the 15th to the 18th week of the semester, and four weeks and 12 h are planned to arrange the DL-themed robot experimental teaching course. In terms of the assessment strategy, a psychomotor scale pre-test will be conducted at the beginning of the semester, followed by a psychomotor scale post-test and affective scale at the end of the semester to verify the feasibility of teaching aids and materials and the reliability and validity of related scales, to evaluate the overall teaching effectiveness. The experimental teaching and teaching assessment process is illustrated in Figure 2.

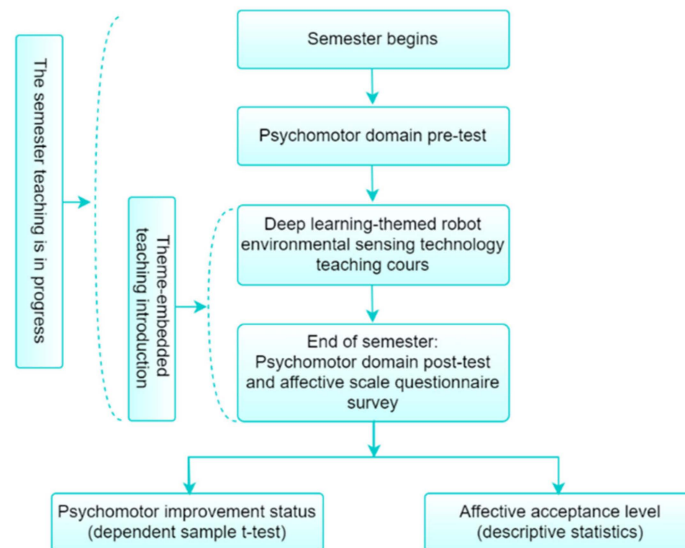


Figure 2. Diagram of the experimental teaching and evaluation process.

3.6. Theme-Based Experimental Teaching and Experimental Teaching Design

3.6.1. Theme-Based Experimental Teaching

The construction of theme-based teaching involves a multi-level, all-round learning design, which can be regarded as a new type of learning paradigm. The teaching strategy model used in this study was integrated into the existing “Automatic Measurement Technology Course”. One advantage of this approach is that it eliminates the need to introduce new courses for assessment, thereby saving time in evaluating already-developed courses. However, a drawback is that the assessment result is only approximate. Certain conditions must be met to implement this teaching strategy. First, both courses must share the same core technology. Second, they should adopt a product-oriented course structure that focuses on building the product at the end of the course. Following this approach can simplify the design and teaching evaluation of robot design and practice courses, as well as the goals of building robots. The reason for using this course for experimental teaching is that LabVIEW and MyRIO are also taught in this course.

3.6.2. Experimental Teaching Design: Quasi-Experimental Design

This study utilized a quasi-experimental design to evaluate the effects of an intervention on a single experimental group without a control group. This study structured the course as a thematic unit, with professional knowledge and equipment thoroughly covered during the first 14 weeks of the semester. As a result, the thematic teaching materials developed may only be appropriate for evaluating the experimental group and not suitable for unequal control groups. This approach poses significant threats to internal validity, it is a limitation of this research method. However, since students were comprehensively trained in the relevant professional knowledge and equipment during the initial 14 weeks, administering the pre-test after this period helped mitigate concerns that students’ professional improvement was solely due to taking this course.

3.7. Evaluation of Teaching Effectiveness and Revision of Teaching Materials and Aids

After conducting the thematic experimental teaching on the robotic environmental monitoring system in DL, a student learning benefit assessment was carried out. The assessment scale included a thematic psychomotor assessment scale and a thematic affective assessment scale. The thematic psychomotor assessment scale adopted the “Robot Design and Practice” course technical ability scoring table developed by Yao et al. [10] and

incorporated technical ability indicators, including hardware structure establishment and hardware and software system integration. The original Kendall's W value of 0.885, a chi-square value of 99.232, and a significant p -value of 0.000, which is less than 0.05.

To understand the students' feedback on the affective aspects of the thematic ML robot teaching course on environmental sensing, after conducting the experimental teaching, a five-point Likert scale was used to assess their affective attitudes in the four aspects of "teaching material and equipment", "cognitive development", "skills performance", and "self-exploration". For the thematic learning affective scale, the questionnaire developed by Yao et al. [10] was used with modifications, and its original reliability test yielded a Cronbach's α of 0.928.

A correlation study on the teaching materials, equipment, and psychomotor assessment scale was conducted to ensure that the skills assessment during the experimental teaching was closely aligned with the teaching objectives and effectively captured student skill development.

In the evaluation of teaching effectiveness, an independent-sample t -test was used to conduct an overall assessment of the psychomotor and affective dimensions. Following the overall assessment, any inappropriate aspects related to programming, techniques, teaching materials, course arrangement, etc., were revised on the basis of the evaluation results. After integrating all feedback and revising the teaching materials, suggestions for the overall assessment at the end of the semester were considered for the final revision of teaching aids and materials to complete the construction of a thematic teaching module on a DL-oriented robotic environmental monitoring system.

4. Results

4.1. Establishment of Technical Ability Indicators and Planning of Teaching Content

This study referred to the technical capability indicators considered in the research results of Yao et al. [10], which included (1) software function design; (2) the use of controllers; (3) hardware structure construction (including I/O equipment); (4) software and hardware system integration; (5) IoT function technology practice; (6) AI module construction (ANN, CNN, and KNN); and (7) system operation. These seven technical capability indicators serve as the basis for the technical capability evaluation scale.

Considering the rapid growth of DL technology, and after expert consultation and a literature review, the theme-oriented curriculum planning of the DL robot teaching module was structured as follows: Chapter 1: Robot Technology (including DL technology); Chapter 2: Software Design; Chapter 3: myRIO Technology; and Chapter 4: DL-themed Robot Design Implementation. The compiled technical capability indicators are listed in Table 1. The 14 technical capability indicators across all four chapters in Table 1 serve as the primary basis for learning evaluation, while the seven indicators in Chapter 4 are the main foundation for curriculum planning in thematic teaching.

Based on the 14 technical capability indicators summarized in Table 1, 15 experts and scholars were invited to complete the FDM questionnaire and participate in interviews. After collecting the questionnaires, the double-triangle fuzzy technique was used to test the degree of consistency. The implementation results are shown in Table 2.

Zi, Mi, and Gi are the parameters of optimistic and conservative triangular fuzzy models [25]. Table 2 presents the data for each item. According to the findings of the convergence state, the expert consensus value Gi was calculated for the evaluation items that completed convergence. From the results of the convergence state in the table, it can be seen that all indicators in this questionnaire reached a consensus among the expert scholars, with no situation where the expert opinions could not effectively converge when $Z_i > M_i$.

The design of theme-based robots and practical courses was planned corresponding to the technical capability index test value ($M_i - Z_i$) and expert consensus value (G_i), as shown in Table 3. Table 4 shows the unit configuration planned for the theme-based DL robot teaching course. This planning mode can be used depending on different DL target themes. As shown in Table 1, Ch 4 focuses on the thematic design and implementation of DL robots, with the curriculum scheduled for four weeks of thematic teaching.

Table 1. Technical capability indicators for DL robotic environmental monitoring module.

Teaching Module Course Planning	Teaching Module Technical Capability Indicators	
Ch1 Robot Technology	1.	Ability to understand the current situation of the robot industry (cognitive part)
	2.	Robot structure and design theoretical capabilities (cognitive part)
	3.	AI and DL technology (cognitive part)
Ch2 Software Design	1.	LabVIEW design capabilities
	2.	Python design ability
Ch3 myRIO Technology	1.	myRIO controller setting and usage capabilities
	2.	System integration capabilities of myRIO controller
Ch4 Thematic Robot Design and Implementation of DL	1.	Robot hardware structure construction capabilities
	2.	Ability to integrate robot hardware structure with sensing and control structures
	3.	Robot software and hardware integration capabilities
	4.	Robot IoT function construction technical capabilities
	5.	Robot AI Modules construction capabilities (ANN, CNN, and KNN)
	6.	Integration and construction capabilities of the robot control system and AI Modules
	7.	Robot system operation capabilities

The technical capability indicators of the first three chapters will also be included in this unit.

Table 2. Technical competence indicators validation values and expert consensus values.

Technical Competence Indicators	Z_i	M_i	Test Value $M_i - Z_i$	Expert Consensus Value (G_i)
1-1 Robot Industry Understanding Capability (Cognitive Part)	1.00	1.78	0.78	8.39
1-2 Robot Structure and Design Theory Capability (Cognitive Part)	2.00	2.36	0.36	7.91
1-3 AI and DL Technology Capability (Cognitive Part)	1.00	1.97	0.97	8.47
2-1 LabVIEW Design Capability	1.00	1.93	0.93	8.29
2-2 Python Design Capability	1.00	1.69	0.69	8.35
3-1 myRIO Controller Configuration and Usage Capability	0.00	2.49	2.49	7.69
3-2 myRIO Controller System Integration Capability	1.00	1.91	0.91	7.50
4-1 Robot Hardware Structure Construction Capability	1.00	2.50	1.50	7.46
4-2 Robot Hardware Structure Integration with Sensing and Control Capability	2.00	2.64	0.64	7.89
4-3 Robot Software and Hardware Integration Capability	2.00	2.48	0.48	7.88
4-4 Robot IoT Function Development Technology Capability	0.00	2.38	2.38	7.96
4-5 Robot AI Modules Development Capability	1.00	2.45	1.45	8.34
4-6 Robot Control System and AI Modules Integration Capability	2.00	2.12	0.12	7.95
4-7 Robot System Operation Capability	2.00	2.05	0.05	7.77

Table 3. Technical capability indicators corresponding to theme-oriented robot design and practical course planning.

Technical Competency Indicators Required for the Design and Implementation of DL-Themed Robots	Theme-Based Robot Design and Practical Course Planning
1-1 Robot Industry Understanding Capability (Cognitive Part)	Current Status and Future of the Robotics Industry
1-2 Robot Structure and Design Theory Capability (Cognitive Part)	Robot Structure and Design
1-3 AI and DL Technology Capability (Cognitive Part)	AI and DL Technology

Table 3. *Cont.*

Technical Competency Indicators Required for the Design and Implementation of DL-Themed Robots	Theme-Based Robot Design and Practical Course Planning
2-1 LabVIEW Design Capability	Program Architecture
2-2 Python Design Capability	Program Architecture
3-1 myRIO Controller Configuration and Usage Capability	Controller Settings
3-2 myRIO Controller System Integration Capability	Controller I/O usage
4-1 Robot Hardware Structure Construction Capability	Hardware Architecture
4-2 Robot Hardware Structure Integration with Sensing and Control Capability	Robot External Connection Device
4-3 Robot Software and Hardware Integration Capability	System Integration and Function Realization
4-4 Robot IoT Function Development Technology Capability	Network Relay Module
4-5 Robot AI Modules Development Capability	Software Architecture
4-6 Robot Control System and AI Module Integration Capability	System Integration and Function Realization
4-7 Robot System Operation Capability	System Integration and Function Realization

Table 4. Unit configuration of DL-themed robot teaching course.

Course Unit	Thematic Robot Design and Practical Course Planning
Unit 1: DL and Robotics	1-1 Current status and future of the robot industry 1-2 Robot structure and design 1-3 AI and DL technology
Unit 2: Architecture of DL for Robotics	2-1 Controller settings 2-2 Input and output use of controller 2-3 Hardware architecture 2-4 Robot external connection equipment 2-5 Network relay module 2-6 Program structure
Unit 3: Establishment and Implementation of DL in Robotics	3-1 System integration 3-2 Function implementation

4.2. Course Teaching Module Equipment Arrangement

This teaching design uses LabVIEW and myRIO to construct a thematic IoT smart home robot teaching module. Figure 3 is the architecture diagram of the smart home environment's data sensing and control prediction system. Figure 4 is the exterior of the IoT smart home robot. The software and hardware are combined to form a DL system for sensing and mobile control. This module uses LabVIEW as the human-machine monitoring interface and Python to build the ANN AI model, embedded in LabVIEW through a Python node for data analysis and prediction. On the other hand, LabVIEW is also responsible for collecting sensor data, including temperature, illumination, humidity, and indoor personnel, and achieves control functions through NI DAQ. After completing the DL system of sensing control and movement control and the AI model of sensing prediction, the system can be embedded in the robot equipment in Figure 5.

The LabVIEW Python node is used to embed the ANN AI model established to predict environmental conditions, as shown in Figure 6. This AI module uses DL technology for data processing and prediction functions. The process can be divided into two steps: training and prediction. Training data are historical data accumulated in the past, consisting of features and labels. After the computer receives the input data, it uses the learning model to output the calculation results. The trained model is used for prediction. New environmental data is input, and the prediction data for the next time point is obtained.

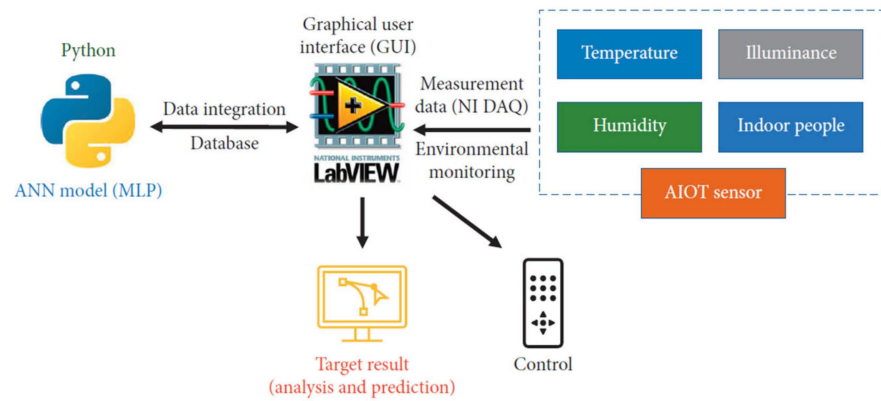


Figure 3. The architecture diagram of the smart home environment's data sensing and control prediction system.

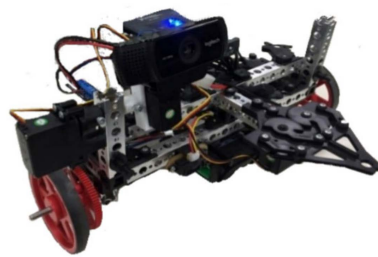


Figure 4. Exterior of the IoT smart home robot.

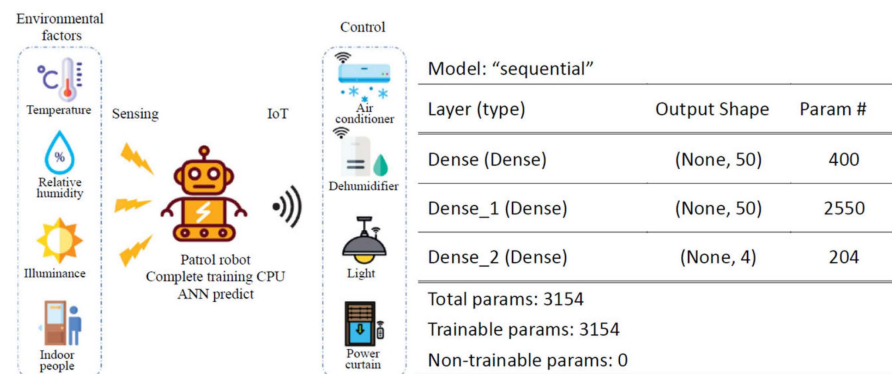


Figure 5. DL AI model system for robot sensing and motion control.

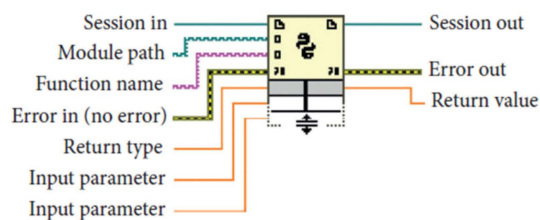


Figure 6. Function block of NI Python node.

In environmental monitoring, an ANN-based AI model built in Python collects and predicts real-time data. These real-time processing and data prediction programs are shown in Figure 7, which compares real-time and predicted data for monitoring the number of people, temperature, humidity, and illumination.

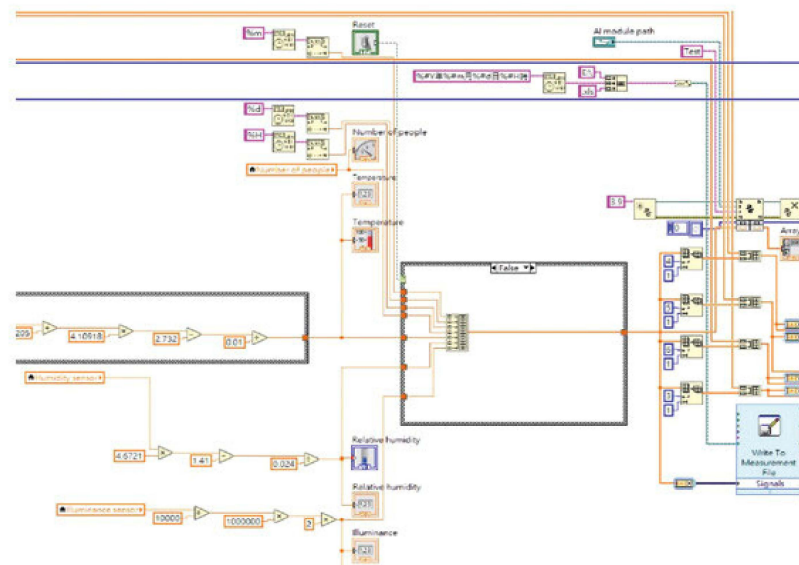


Figure 7. Diagram of real-time processing and data prediction.

We employed DL methods to forecast environmental conditions, a subset of AI. To enhance the learning efficiency of the AI model, the learning process is typically split into two phases: training and testing. During the training phase, historical data containing features and labels are utilized. Following the testing process of the AI model, it can generate predictions. The AI learning model functions similarly to the brain of an AI system. A more complex neural network model must be constructed to develop a more intelligent machine. The construction procedure is illustrated in Figure 8.

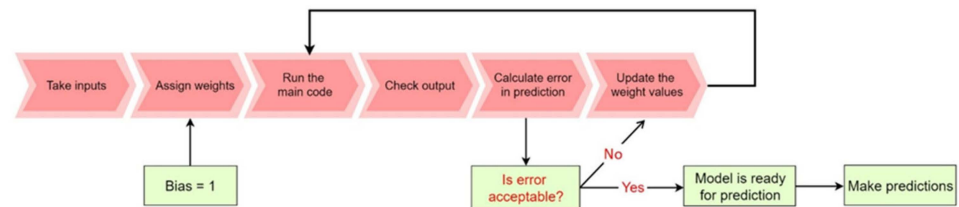


Figure 8. Flowchart of ANN design.

The learning model created in this research employs an Artificial Neural Network (ANN) for environmental forecasting. Within the ANN are numerous neurons with distinct functions; some receive data, while others transmit it. The ANN-MLP model utilized in this study is depicted in Figure 9.

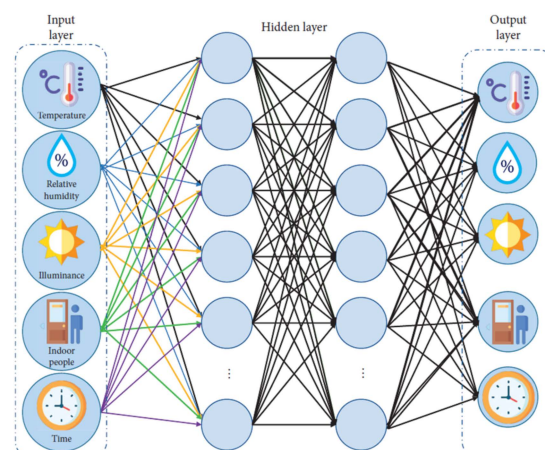


Figure 9. ANN-MLP model architecture.

4.3. Teaching Strategies and Evaluation

The diagram of the experimental teaching and evaluation process is shown in Figure 2. The evaluation process was deployed during the semester. This designed module aimed to be practically applied in embedded courses for teaching experiments. The psychomotor evaluation scale assessed learners' skills performance, while the affective evaluation scale gauged students' emotional feedback regarding the teaching of the embedded IoT smart home robot. After the experimental teaching, four dimensions—teaching materials and equipment, cognitive development, skills performance, and self-exploration—were used to evaluate the emotional attitudes of the students in the experimental group using a five-point Likert scale.

This study's learning benefit assessment scale included a thematic psychomotor assessment scale and a thematic affective scale (Appendix A). The thematic psychomotor assessment scale was adopted from the research of Yao et al. [10]. This study considered some indicators in the developed evaluation scale, including software design, controller use, hardware construction, software and hardware system integration, IoT technology practice, system operation, etc. This integration improves skills. To assess the accuracy of the scale, the two evaluation scales were used in automatic measurement technology courses, evaluating the effectiveness of thematic teaching in robot design and practice courses.

The psychomotor assessment scale in this study was adopted from Yao et al. [10]. The original Kendall's W of the scale was used to test the consistency and reliability of the ratings of the three teachers. The results showed that Kendall's W was 0.885; the chi-square value was 99.232; the p -value was less than 0.05, showing significance; and Cronbach's α reliability was 0.928. This study added technical ability indicators of Python and AI model (ANN and CNN) building capabilities, and the revised skills evaluation scale is shown in Appendix A. The skill scores of the pre- and post-tests were conducted on the basis of the skills assessment scale of the Environment Sensing ML Themed Robot Teaching Course. Each aspect was evaluated using a 5-point Likert scale. The total score of the evaluation form is 50 points. Each question was scored as follows: very good = 5, good = 4, fair = 3, poor = 2, and very poor = 1, for a total score of 10 to 50.

Pre-tests and post-tests were conducted using paired-sample t -tests to assess the effectiveness of the developed teaching materials and devices in improving students' skills performance. In the pre-test, Kendall's W was used to test the consistency and reliability of the three teachers' ratings. The results showed a Kendall's W of 0.879, a chi-square value of 99.315, and a significance level of $p < 0.05$, confirming the consistency of the grading. Table 5 presents the statistical results of the paired-sample t -test for skills performance. Table 6 details the differences between pre-test and post-test scores and the t -test results, showing an average difference of $M = -25.02$. The t -test result was $t = -38.177$, with $df = 37$ and a significance level of 0.001. These results indicate that students significantly improved their skills performance after taking the course.

Table 5. The paired-sample t -test results.

Paired Variables	N	M	SD	SE	t
Pre-test	38	15.82	1.92	0.29	−38.177 ***
Post-test	38	40.53	5.08	0.79	

*** $p < 0.001$.

Table 6. Paired-sample difference of *t*-test.

Item		Paired Difference					<i>t</i>	<i>df</i>
		M	SD	SE	95% CI			
					UL	LL		
Paired Sample	Pre-test Post-test	−25.02	3.92	0.47	−25.23	−19.96	−38.177 ***	37

Remark: CI = Confidence Interval; UL = Upper Limit; LL = Lower Limit; *** $p < 0.001$.

After finding that the 38 students' skills performance improved after receiving experimental teaching, the reliability of the skills assessment in the pre-test and post-test was tested using Kendall's W concordance coefficient. The value of Kendall's W concordance coefficient was 0.885; the chi-square value was 99.017; the *p*-value was significant (0.000), as it was less than 0.05; the Cronbach's α reliability was 0.931, there was a significant correlation between the scores of the three reviewers, and the results were highly consistent. Table 7 presents the average and standard deviation of each level of technical ability assessment for students who received environmental sensing ML-themed robotics teaching courses.

Table 7. Pairwise differences in each level of technical ability assessment in environmental sensing ML-themed robot teaching courses.

Dimension	Question Number	N	M	SD	M/D	Sort
(1) Robot equipment assembling ability	2	38	−4.58	0.80	−2.44	4
(2) Robot equipment operation ability	3	38	−8.17	0.84	−2.61	3
(3) Robot equipment integration ability	1	38	−3.21	0.49	−3.19	2
(4) Robot design ability	4	38	−13.38	0.88	−3.45	1
Total scale	10	38	−28.85	1.75	−2.92	

After the experimental teaching, an emotional attitude assessment was conducted to understand the students' affective feedback for the environmental sensor DL-themed robot teaching course. The affective evaluation scale was based on the scale developed by Yao et al. (2020). The original Cronbach's α reliability of the scale was 0.902, indicating good internal consistency reliability, which is the reason the affective scale was used in this study. This study adjusted and modified the subject teaching of the affective scale developed by Yao et al. [26], focusing on IoT smart home robots.

The affective scale was designed as a 5-point Likert scale, consisting of strongly agree, strongly agree, neither agree nor disagree, tend to disagree, and strongly disagree. After the experimental teaching, the affective attitude assessment was structured around the following four aspects: "teaching materials and teaching aids", "cognitive behavior", "skills performance", and "self-exploration". In the last week of the course, 38 students completed the questionnaire and expressed their feelings. All questionnaires were collected (recovery rate: 100%). The reliability test measured by the formal questionnaire revealed a Cronbach α of 0.915, indicating excellent internal consistency. The statistical results of the average and standard deviation of each aspect of the affective questionnaire for students who received the environmental sensing DL-themed robot teaching course were as follows:

- (1) Teaching material and equipment (Table 8).
- (2) Cognitive development (Table 9).
- (3) Skills performance (Table 10).
- (4) Self-exploration (Table 11).

The average values of each dimension are 4.15, 4.33, 4.57, and 4.68; the average reaches 4.52, and the results show that these four Dimensions tend to be consistent. It can be observed that students have the highest positive feelings in the self-exploration stage, followed by skill learning, cognitive needs, and teaching aids and materials. The qualitative survey revealed that students needed robot design, practical technology, and its development trends. The students themselves expressed an interest in learning AI, AI module construction, and intelligent robot construction. Therefore, these professional knowledge and skills will be relevant to actual work in industries such as smart robots and artificial intelligence, which may be pursued in the future.

Table 8. Mean value and standard deviation for the teaching material and equipment.

No.	N	M	SD
(1) The teaching material content is correct and easy to read.	38	4.00	0.58
(2) The content amount and difficulty are appropriate.	38	4.45	0.61
(3) The teaching material content is logical and well-organized.	38	4.05	0.51
(4) The teaching material has a good connection with the teaching.	38	4.35	0.63
(5) The teaching material and experimental equipment contain enough knowledge and practice.	38	4.35	0.49
(6) The teaching material and experimental equipment can clearly explain the experimental process.	38	4.10	0.53
(7) The teaching material and experimental equipment can integrate other related professional knowledge to solve the problems.	38	4.15	0.62
Teaching material and equipment	38	4.15	0.33

Table 9. Mean value and standard deviation for the cognitive development dimension.

No.	N	M	SD
(1) The goal of each chapter clearly expresses the critical learning points.	38	4.10	0.59
(2) The teaching material can help me learn many new professional concepts in this field.	38	4.00	0.65
(3) The teaching material contains innovative skill content.	38	4.00	0.63
(4) The teaching material can enhance my application ability.	38	4.05	0.66
(5) The teaching material and experimental equipment stimulate personal learning motivation and interest.	38	4.35	0.45
(6) The teaching material and experimental equipment correspond with the teaching goals of this course.	38	4.45	0.58
(7) The teaching material and experimental equipment inspire me to develop new products.	38	4.50	0.63
Cognitive development	38	4.33	0.28

Table 10. Mean value and standard deviation for the self-exploration dimension.

No.	N	M	SD
(1) The skills training in this course matches industry needs.	38	4.25	0.61
(2) This course contains professional skills and knowledge of robot design and practice.	38	4.09	0.63
(3) The skills training in this course matches the skill needs of industry robot design and practice.	38	4.24	0.67
(4) This course can help me understand industry robot design and practice trends.	38	4.03	0.59
(5) This course helps me to understand if I fit this professional field.	38	4.12	0.51
(6) This course increases my practical experience in robot design and Practice.	38	4.35	0.63
(7) The course offers a personal and professional advantage for future jobs.	38	4.620	0.67
Skills performance	38	4.57	0.28

Table 11. Mean value and standard deviation for the skills performance dimension.

No.	N	M	SD
(1) The course helps to increase the ability of robot design.	38	4.55	0.43
(2) The course and teaching materials excite me to apply to LabVIEW programming.	38	4.80	0.57
(3) The course promotes personal knowledge and skills in understanding myRIO controllers.	38	4.58	0.46
(4) The course and teaching materials can improve practical skills in robot construction.	38	4.45	0.43
(5) This course can help students increase robots' innovative development ability.	38	4.90	0.45
(6) The teaching material and experimental equipment provide students with practical support for the current learning demand needed in the industry.	38	4.35	0.45
(7) This course promotes personal multi-dimensional professional skills.	38	4.75	0.48
Self-exploration	38	4.68	0.31

Table 12 shows the analysis table of *t*-tests for students' attitudes toward different graduation plans. This shows that students interested in further education are more proactive in their cognition and skills. Conversely, students who plan to enter the workforce may be less involved in coursework due to obligations such as military service and internships. However, as shown in Tables 8–10, the overall feedback from students who participated in the course was very positive at all levels of the emotional questionnaire.

Table 12. Analysis table of *t*-tests for students' attitudes toward different graduation plans.

Dimension	No.	Graduation Plan	N	$\bar{x}$	SD	<i>t</i>	<i>p</i>
(1) Teaching material and equipment	7	Graduate Employment	14 24	4.54 4.49	0.531 0.547	1.599	0.112
(2) Cognitive development	7	Graduate Employment	14 24	4.82 4.23	0.586 0.485	3.582 ***	0.000
(3) Skills performance	7	Graduate Employment	14 24	4.77 4.52	0.428 0.409	3.917 ***	0.000
(4) Self-exploration	7	Graduate Employment	14 24	4.86 4.39	0.562 0.634	1.798	0.156
Total	28	Graduate Employment	14 24	4.62 4.53	0.518 0.499	3.158 **	0.005

SD: Standard deviation; $\bar{x}$: Arithmetic mean; N: Number of people; N = 38; $p^* < 0.05$; $p^{**} < 0.01$; $p^{***} < 0.001$.

5. Conclusions

1. This study focused on organizing intelligent courses and theme-based teaching of DL robots, thereby emphasizing learners' technical capabilities. After an extensive literature review, technical ability indicators were planned and tested using the FDM's double triangle fuzzy numbers and gray areas to integrate expert opinions. Through this analysis, technical capability indicators were established on the basis of the consensus of experts and scholars to enhance the unit configuration of the planned DL robot intelligence thematic teaching course.
2. This research used virtual instrument technology and LabVIEW software to develop a smart home system that integrates a servo host, myRIO controller, and robotic devices. The ANN AI model, developed in Python, was incorporated into the LabVIEW system for mobile control and sensor data monitoring to enhance the DL system. This combination exploits LabVIEW's powerful monitoring interface and Python's robust AI algorithm capabilities. This study successfully implemented environmental sensing and prediction for smart home robots and developed themed teaching modules for a DL-oriented robotic environmental monitoring system.
3. This study aimed to plan and implement teaching modules on DL smart home robots and theme-based teaching experiment strategies and evaluate the effectiveness of these DL robot design and implementation courses. Skill (psychomotor) and affective scales were developed to assess learning effectiveness. The post-test results showed significantly better scores than the pre-test results, indicating effective improvement in learners' overall technical abilities and skill levels. The affective domain assessment covered four dimensions. (1) Teaching materials and equipment: The content was correct, easy to read, well-organized, logical, and provided adequate knowledge and practice. The experimental section clearly explained the processes. (2) Cognitive development: The chapter objectives clearly expressed a learning focus, and the materials stimulated personal motivation and interest. (3) Skills performance: The courses and materials improved practical skills in robot construction. (4) Self-exploration: The course enhanced practical experience in robot design and helped learners understand their suitability for this field. Based on these results, this study successfully established thematic teaching modules and assessment models.
4. Students' future development was further evaluated, and the results revealed very positive feedback across all levels of the affective scale for those who participated in the theme-based teaching experiment. Students who wished to continue their studies demonstrated significantly better skills and more positive emotional attitudes, contributing to a higher overall positive experience.

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Appendix A

Table A1. Psychomotor scale form.

Dimension 1: Robot equipment assembling ability	Grading (very good: 5, good: 4, neutral: 3, poor: 2, very poor: 1)				
1. MyRIO controller setting and testing (Explanation: Correct MyRIO controller setting and successful communication with computer)	5 ☐	4 ☐	3 ☐	2 ☐	1 ☐
2. Robot structure assembling (Explanation: Robot structure assembling including controller reasonable displacement)	☐	☐	☐	☐	☐
Dimension 2: Robot equipment operation ability (Explanation: Abilities to use LabVIEW and I/O of MyRIO controller)					
1. Front panel operation ability of LabVIEW	5 ☐	4 ☐	3 ☐	2 ☐	1 ☐
2. Block diagram operation ability of LabVIEW	☐	☐	☐	☐	☐
3. I/O Utilization ability of MyRIO controller	☐	☐	☐	☐	☐
Dimension 3: Robot equipment integration ability					
1. Integration ability of software and hardware (Explanation: Order, wiring correction, and controllable system)	5 ☐	4 ☐	3 ☐	2 ☐	1 ☐
Dimension 4: Robot design ability (Explanation: Creativity and structure assessment on program and function)					
1. LabVIEW program design—Creativity	5 ☐	4 ☐	3 ☐	2 ☐	1 ☐
2. LabVIEW program design—Function	☐	☐	☐	☐	☐
3. Robot structure design—Creativity	☐	☐	☐	☐	☐
4. Robot structure design—Function	☐	☐	☐	☐	☐

Table A2. Affective scale form of thematic IoT smart home robot course.

Dimension 1: Teaching material and equipment		5	4	3	2	1
1	The teaching material content is correct and easy to understand.	☐	☐	☐	☐	☐
2	The amount of content and difficulty level are appropriate.	☐	☐	☐	☐	☐
3	The teaching material content is logical and well-organized.	☐	☐	☐	☐	☐
4	The teaching material is well-connected with the teaching.	☐	☐	☐	☐	☐
5	The teaching material and experimental equipment contain enough knowledge and practice.	☐	☐	☐	☐	☐
6	The teaching material and experimental equipment can clearly explain the experimental process.	☐	☐	☐	☐	☐
7	The teaching material and experimental equipment can integrate other related professional knowledge to solve problems.	☐	☐	☐	☐	☐

Table A2. Cont.

Dimension 2: Cognitive development					
1	The goal of each chapter clearly expresses the key learning points.	☐	☐	☐	☐
2	The teaching material can facilitate the learning of new professional concepts in this field.	☐	☐	☐	☐
3	The teaching material contains innovative skill content.	☐	☐	☐	☐
4	The teaching material can improve application ability.	☐	☐	☐	☐
5	The teaching material and experimental equipment stimulate personal learning motivation and interest.	☐	☐	☐	☐
6	The teaching material and experimental equipment correspond with the learning objectives of this course.	☐	☐	☐	☐
7	The teaching material and experimental equipment inspire students to develop new products.	☐	☐	☐	☐
Dimension 3: Skills performance					
1	Thematic IoT smart home robot course helps increase AI robot design ability.	☐	☐	☐	☐
2	Thematic IoT smart home robot course teaching materials encourage students to apply LabVIEW programming.	☐	☐	☐	☐
3	Thematic IoT smart home robot course promotes personal knowledge and skills concerning myRIO controller.	☐	☐	☐	☐
4	Thematic IoT smart home robot course can improve practical skills in robot construction.	☐	☐	☐	☐
5	Thematic IoT smart home robot course can help students improve their innovative development ability of robot construction.	☐	☐	☐	☐
6	Thematic IoT smart home robot course teaching material and experimental equipment provide students with practical support to meet the current learning demands of the industry.	☐	☐	☐	☐
7	Thematic IoT smart home robot course promotes personal multidimensional professional skills.	☐	☐	☐	☐
Dimension 4: Self-exploration					
1	The skills training offered in this thematic course matches industry needs.	☐	☐	☐	☐
2	This thematic course imparts professional skills and knowledge on robot design and practice.	☐	☐	☐	☐
3	The skills training in this thematic course matches the industry's skill requirements for robot design and practice.	☐	☐	☐	☐
4	This thematic course can help students understand the current trends and practices in the robot design industry.	☐	☐	☐	☐
5	This thematic course helps students understand if they are suited for this professional field.	☐	☐	☐	☐
6	This thematic course increases students' practical experience in robot design and practice.	☐	☐	☐	☐
7	This thematic course offers a professional advantage for future employment.	☐	☐	☐	☐

(very good: 5, good: 4, neutral: 3, poor: 2, very poor: 1).

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