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A Big-Data-Based Experimental Platform for Green Shipping Monitoring and Its Teaching Application

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Abstract: The construction of New Business Studies (NBS) in China and big data technology offer an opportunity for teaching reform. Based on the existing teaching resources, professional knowledge, data, and technology, we monitored the dynamics and checked the statistics of air pollutant emissions from ships in global waters. Various techniques of big data analysis and methods of artificial intelligence were employed, including data collection, data fusion, feature analysis, deep learning network, and system testing. Specifically, the scenario of green shipping monitoring was reproduced by virtual reality; experimental learning was carried out, involving five experimental methods, eight experimental steps, and ten interactive operations; and the results of the experimental learning were assessed. In this way, the students had a better cognition of datasets, a deeper understanding of data correlation, and an improved mastery of interactive operations. In addition, the students varied in terms of learning performance, experimental participation, and active performance inspired by individual thinking. Overall, the students were satisfied with the quality of experimental learning.

Keywords: big data technology; teaching method reform; teaching effect evaluation; green shipping; experimental learning

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1. Introduction

In 2018, the Chinese Ministry of Education proposed the initiation of the New Business Studies (NBS). The construction and development of the NBS not only necessitate the establishment of innovative, comprehensive, and full-cycle "new ideas" in business education, but also propose new requirements for higher education and teaching, encompassing construction concepts, training criteria, and innovative approaches [1–3]. The NBS construction places emphasis on industry orientation, with a focus on nurturing business professionals with data intelligence at their core. Our university is a specialized institution of higher education with industry characteristics, dedicated to cultivating high-quality maritime talents. In our educational framework, we consistently emphasize industry and application-oriented characteristics. We build upon and enhance our advantages and unique qualities in the field of maritime transportation. We implement a multidisciplinary and practical teaching curriculum system with an interdisciplinary approach in business-related majors, aiming to develop maritime professionals with fundamental skills and proficiency in information technologies, aligning with the talent requirements in the era of NBS construction. In the new era, the development of big data technology has significantly influenced teaching and research endeavors in global maritime transportation [4–6]. The International Maritime Organization (IMO) is actively promoting the gradual transformation of the global shipping industry towards greener and more intelligent practices [7,8]. These development trends pose new challenges to talent cultivation in maritime institutions, demanding professionals equipped with knowledge and skills in sustainable shipping development, data intelligence technology, and other relevant areas.

To cultivate well-rounded professionals oriented towards internationalization, digitalization, and sustainable development, universities are continuously deepening practical teaching reforms through measures such as encouraging faculties to apply for grants relevant to teaching reform, establishing collaborative experimental teaching bases between the university and enterprise, and building joint training platforms for innovative talents [1–10]. Our team has collaborated with ELANE, a Beijing-based company specializing in shipping data, to develop a green shipping monitoring experimental platform based on fundamental knowledge and representative data. The integration of this experimental platform with the existing curriculum system has transformed the education of courses such as Green Shipping Economics, Computational Mathematics, Green Supply Chain Management and Practice, and Shipping Supply Chain Operation Management from traditional teacher-centered methods to student-centered methods. Specifically, in terms of course design, interactive teaching segments based on the experimental platform have been incorporated to enhance student engagement in learning. The focus on acquiring fundamental experimental knowledge and basic skills has been enhanced in the teaching content. As for teaching methods, mobile technology has been utilized as a new source for knowledge expansion and construction, with an emphasis on developing micro-courses, online courses, and course websites [11,12]. Assessment methods for experimental courses have become more diverse, including the evaluation of experimental operations and reports as part of the overall grades. This type of teaching methodology aligns with the training goals of project-based learning and challenge-based learning, effectively enhancing students' abilities in self-directed learning, problem solving, and teamwork [13,14].

Drawing on existing teaching resources, professional knowledge, databases, and technology, we employed big data analysis techniques, artificial intelligence methods, and virtual reality technology to establish a green shipping monitoring experimental platform through university–enterprise collaboration. The implementation of this experimental platform in teaching endeavors aims to drive curriculum reform and foster well-rounded maritime professionals. Specifically, various methods such as data collection, data integration, feature analysis, and deep learning networks were adopted to test the system, enabling the dynamic monitoring, accounting, and statistical analysis of air pollution. To enrich and diversify the teaching content with the help of big data technology, we designed teaching content and methods based on the experimental platform. These encompass five experimental methods, eight experimental steps, and ten interactive operations. Additionally, we assessed their effectiveness on students' cognition of datasets, understanding of data correlations, and mastery of interactive operations. This study offers several key contributions:

1. By utilizing technologies such as big data analysis, artificial intelligence, and virtual reality, we successfully built up a green shipping monitoring experimental platform through university–enterprise collaboration. This platform forms the basis for a student-centered, output-oriented, and quality-focused teaching model. Supported by big data, this teaching model integrates theory and practice together, with a strong emphasis on practical courses. It represents a distinct departure from previous teaching reform in business-related majors, presenting an integrative and coherent teaching mode that revolutionizes practical teaching in the context of NBS construction.
2. A diversified range of teaching content and methods was established based on the proposed experimental platform. By conducting experiments with undergraduate and graduate students enrolled in relevant courses, we validated the significant effects of integrating practical teaching and experimental learning. The teaching content and methods designed in this study represent a novel and pioneering endeavor. They not only serve as a teaching paradigm for curricular reforms in

other disciplines but also align with the talent development trends in the context of NBS construction.

2. Literature Review

In response to the new situation of development, scholars have undertaken research on practical teaching reforms aimed at expediting the shift from the teacher-centered teaching mode into a student-centered teaching mode. The objective is to nurture talents who not only possess professional knowledge but also exhibit the capacity to discover, investigate, and solve problems. To illustrate, Yao et al. [15] implemented a teaching method reform for the C programming course through the lens of sustainable development. Their approach encompassed theoretical classes, practical training sessions, and innovative practice sessions, culminating in a student-centered teaching model characterized by "three classrooms–four integrations–five combinations". Similarly, Chi et al. [16] reformed the traditional teaching methods of marketing courses in universities. They conducted marketing practices based on two different Internet algorithm-driven marketing strategy models.

To further foster innovative practical talents, practical teaching reforms frequently combine with platform construction and university–enterprise collaborations. For instance, Wang et al. [17] constructed an innovative education platform for the education and training system of intelligent manufacturing talents, enhancing the linkage between theoretical learning and practical applications. Xi et al. [18] proposed a practical ability training platform centered on "university–enterprise co-operation", leveraging the alignment of engineering education requirements between academic institutions and enterprises. Their approach integrated enterprise teaching mechanisms with the aim of cultivating practical abilities. Focusing on the analysis and mining of car networking data, He et al. [19] conducted theoretical research and engineering verification of the driving behavior economy. They adopted a learning method that incorporates teacher-guided theoretical research and enterprise-guided engineering practice.

Against the backdrop of the new technological revolution, characterized by advancements in big data, artificial intelligence, mobile internet, cloud computing, and blockchain, the convergence of emerging technologies and education undoubtedly presents new challenges to the thinking patterns in education. Tian et al. [20] analyzed the reform and adjustment of the computer education curriculum based on the B5G model and online education model, before proposing specific reform strategies. Liu et al. [21] developed a teaching design model that combines big-data flipped classrooms with scenario simulation in medical clinical practice, exploring the application and effectiveness of this teaching method. Building on advanced big data technology, Wu [22] proposed an optimization method for a macroeconomics teaching model based on cluster analysis. The feasibility of this model was verified through the creation of teaching scenarios and practical teaching applications.

The integration of digital technology in the construction of teaching systems holds significant potential to enhance teaching efficiency and advance intelligent instruction. For example, Guo [23] utilized data from a long short-term memory (LSTM) network management platform to address the issue of memory mechanisms in the current teaching system. Through this approach, dispersed teaching information was effectively integrated, fostering the development of information-based teaching. Tang et al. [24] introduced data mining technology to educational reform, constructing a tailored computer-aided system based on data mining to cater to specific needs. Likewise, Cao [25] reformed teaching practices by developing an intelligent modern classroom teaching system for ideological and political courses, capitalizing on artificial intelligence and internet technology.

After combing through these representative studies, we compared this study with the literature from several aspects, including business education reform, experimental platform construction, practical teaching reform, and emerging technology application, as shown in Table 1. On this basis, this study proposes an innovative approach to the teaching reform of the NBS construction in China. Specifically, an experimental platform for green shipping monitoring was built through university–enterprise collaboration, integrating big data analysis, artificial intelligence, and virtual reality. The platform helps to cultivate well-rounded maritime talents with a global vision and professional expertise through practical teaching reform.

Table 1. Comparison with related studies.

Literature	Business Education Reform	Experimental Platform Construction	Practical Teaching Reform	Emerging Technology Application
Yao et al. [15]			√	
Chi et al. [16]	√		√	
Wang et al. [17]		√	√	
Xi et al. [18]		√	√	
He et al. [19]		√	√	√
Tian et al. [20]				√
Liu et al. [21]			√	√
Wu [22]	√		√	√
Guo [23]				√
Tang et al. [24]				√
Cao [25]				√
This paper	√	√	√	√

The symbol "√" indicates that this aspect is included.

3. Deep-Learning-Based Experimental Platform

We firstly identified the experimental needs of many courses in our university related to shipping, greenness, environment, and sustainability, including postgraduate courses in the disciplines of transportation planning and management, transportation, and business administration, and undergraduate courses in the disciplines of supply chain management and logistics management. On this basis, our experimental platform for green shipping monitoring employs deep learning to correlate the real-time activities of various ships transporting cargo at home and abroad with the emissions of six air pollutants (CO_2, CO, SO_X, NO_X, PM, and CH_4) in the major sea areas around the world. Further, we established an online estimation model for the air pollutant emissions of ships based on a deep convolutional neural network (DCNN). From the angles of ship type, trade route, and major port, the relevant data were visually collected and analyzed.

3.1. Data Collection

The IMO adopted the Ship Traffic Emission Assessment Model (STEAM) to measure the air pollutants emitted by ships [26]. Referring to this model, we selected the data for our experimental platform from the automatic identification system (AIS) database of ships, the aerosol database of the National Aeronautics and Space Administration (NASA), and the Copernicus Marine Atmospheric Monitoring Service (CMEMS). The original dataset covers the period from 1 December 2019 to 30 June 2022. As shown in Figure 1, the following global sea areas frequently visited by ships were selected: the eastern coast of China (29–41° N, 119–127° E), the Bay of Bengal of India (0–20° N, 80–100° E), the western coast of Europe (40–50° N, 5–20° W), the waters around Cape Verde (10–25° N, 20–40° W), and the eastern coast of the United States (26–41° N, 70–80° W).

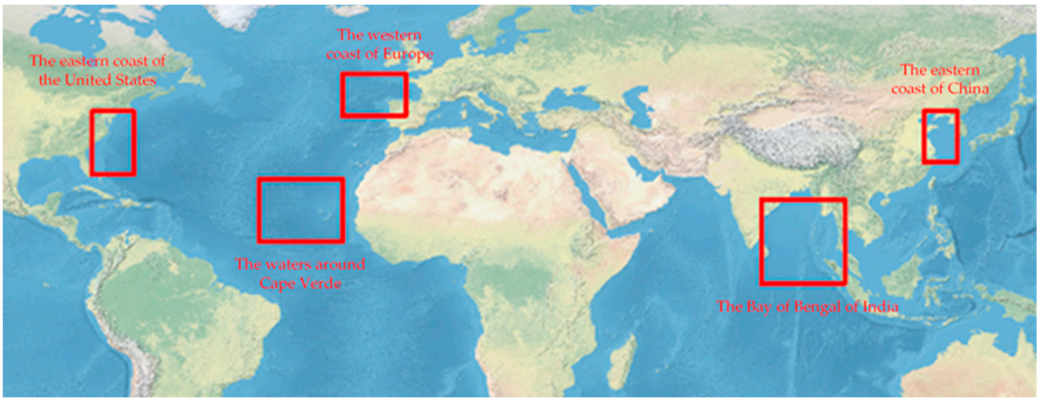

Figure 1. Selected sea areas.

3.1.1. AIS Data

The data from the AIS record the real-time positions of 350,000 ships worldwide, including dry bulk carriers, tankers, and container ships, and cover the sea areas of nearly 180 countries. The AIS data for our experimental platform were provided by ELANE, which can collect data based on mobile technology and can be deployed in stations at different locations to cover shore-based, satellite-based, and vessel-based data sources. The attributes of these AIS data are presented in Table 2.

Table 2. AIS data attributes.

Attribute	Description
Date, Time	Date and time
LAT, LON	Latitude and longitude (in degrees)
SOG, COG	Speed over ground, and course over ground (in nautical miles, and degrees)
Length, Width	Ship length, and ship width (in meters)
Draught	Draught depth (in meters)

3.1.2. Aerosol Data

Air pollutants emitted by ships are a major source of aerosols over the sea. The most important parameter of these aerosols is aerosol optical depth (AOD). The aerosol data of our experimental platform were obtained from the historical dataset collected by the moderate resolution imaging spectroradiometer (MODIS) onboard NASA satellites. Table 3 displays the attributes of these aerosol data.

Table 3. Aerosol data attributes.

Attribute	Description
Date, Time	Date and time
LAT, LON	Latitude and longitude (in degrees)
AOD (550 nm)	Aerosol optical depth

3.1.3. Marine Meteorological Data

Marine meteorology directly bears on the fuel consumption of a navigating ship, and determines the concentration of pollutants emitted from the ship. The marine meteorological data of our experimental platform were collected from the dataset of CMEMS. Table 4 shows the attributes of these data.

Table 4. Marine meteorological data attributes.

Attribute	Description
Date, Time	Date and time
LAT, LON	Latitude and longitude (in degrees)
NC, EC	Longitudinal and latitudinal current velocities (in meters/seconds)
Temperature	Water temperature (in degrees Celsius)
WaveHeight	Wave height (in meters)

3.2. Data Fusion

The data from the above three sources need to be consistent in time and space to form a complete dataset called "ship AIS–marine meteorology–sea air pollution" [27]. The original datasets have three common attributes: time (Time), longitude (LON), and latitude (LAT). These attributes were unified in format, and taken as the primary keys to match the three original datasets. The data fusion process is illustrated in Figure 2.

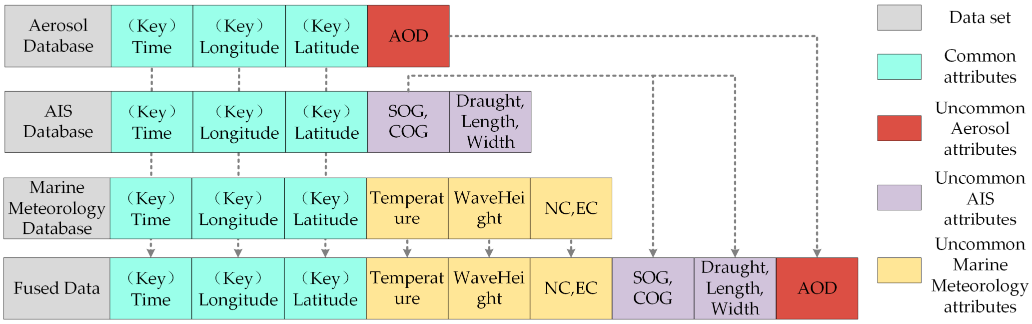

Figure 2. Process of data fusion.

Based on the original datasets, a three-layer feedforward back propagation neural network (BPNN) model is established, with data fusion for input. The training function in the BPNN model is the Bayesian regularization algorithm. The weights and biases are updated according to the Levenberg–Marquardt method of least squares estimation of regression parameters. Each neuron in the hidden layer has a sigmoid function to convert the input, and the neuron in the output layer uses a linear function to convert.

The sigmoid function is a logarithmic tangent function, and its expression is:

$$y = f(u) = \frac{1}{1 + e^{-\lambda u}}. \tag{1}$$

where the parameter is the gain of the sigmoid function, that is, the slope parameter. The larger the value of λ, the steeper the curve.

The linear function expression is as follows:

$$y = f(u) = u. \tag{2}$$

The fused dataset has 88,753 valid data, including 12 attributes: time (Time), longitude (LON), latitude (LAT), water temperature (Temperature), wave height (WaveHeight), longitudinal and latitudinal current velocities (NC, EC), speed over ground (SOG), course over ground (COG), draught depth (Draught), ship length (Length), ship width (Width), and aerosol optical depth (AOD).

3.3. Feature Analysis

Figure 3 shows the correlations of AOD–speed–NC, EC, AOD–displacement, AOD–water temperature, and AOD–wave height. The red dashed lines and blue solid lines represent original values and fitted smooth curves, respectively. Sea air pollution has complex nonlinear correlations with time, SOG, NC, EC, displacement (ship length, ship width, and draught depth), water temperature, and wave height. As a result, it cannot be easily estimated by traditional data fitting, which relies on the implicit relationship between ship AIS and marine meteorology.

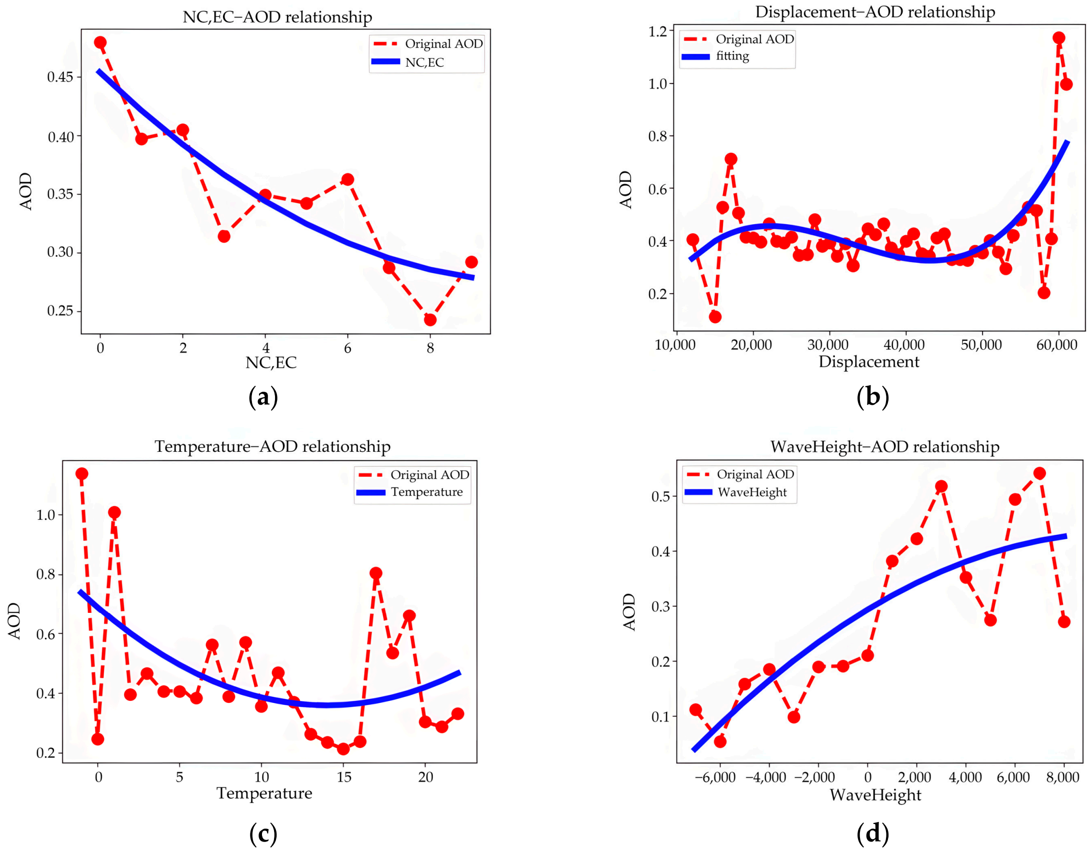

Figure 3. Correlations between AOD and different features: (**a**) AOD–speed–NC, EC relationship; (**b**) AOD–displacement relationship; (**c**) AOD–water temperature relationship; and (**d**) AOD–wave height relationship.

3.4. Deep Learning Network

Our deep learning network was built under the framework of TensorFlow. It is a DCNN, a multilayer artificial neural network specifically designed for processing multidimensional data [28,29]. As shown in Figure 4, the experimental platform stacks four segments of network layers.

The first segment consists of two convolutional layers and one max pooling layer. In the first convolutional layer, there are eight 1×1 kernels with a step size of 1. In the second convolutional layer, there are sixteen 2×1 kernels with a step size of 2. The last layer in this segment, i.e., the max pooling layer, has a step size of 1.

The second, third, and fourth segments have a similar structure as the first segment. The only difference is that the first convolutional layer of the second, third, and fourth segments has four, 16, and 32 kernels, respectively; while the second convolutional layer of the second, third, and fourth segments has eight, 32, and 64, respectively.

The pooled results, which are multidimensional, are imported to the flatten layer, and converted to one-dimensional results via Dropout regularization. Finally, the local information is merged at the dense, fully connected layer. Through summation and activation, the network outputs a multiscale time series of sea air pollution based on "ship AIS–marine meteorology".

The feature map and channel attention are used to extract the spatio-temporal features to balance the hidden features to enhance the effectiveness of the features.

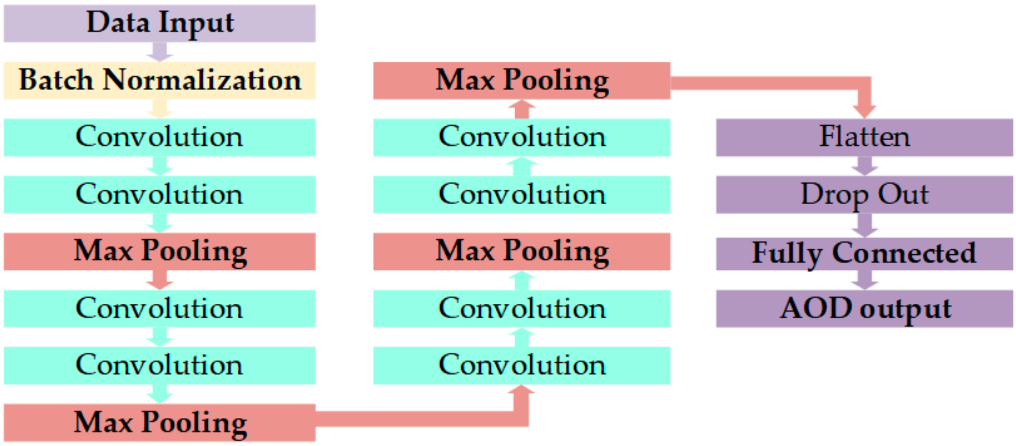

Figure 4. Sketch map of our neural network. Blocks in different colors represent different processes.

In the feature map model, the convolution kernel is used for the convolution operation to obtain the mapping of the output spatiotemporal features. $F = \{f(1), f(2), \ldots, f(j)\}$ is the output hidden feature mapping of the convolution layer; that is, $j \in R$ is the number of convolution cores. This is carried out by the equation:

$$\omega_i = \frac{\exp(f(i))}{\sum_{t=1}^{j} \exp(f(t))}, \tag{3}$$

$$F' = W \odot F. \tag{4}$$

where $W = \{\omega_1, \omega_2, \ldots, \omega_j\}$ is a group of weight matrices, same as feature mapping. $\odot$ is the product of elements. The attention model generating W is composed of multiple convolution layers.

For the input hidden feature mapping $F = \{f(1), f(2), \ldots, f(j)\}$ of the channel attention model, j is the number of channels in the feature mapping, and the maximum pooling operation is performed in F to obtain the maximum value of each channel $C = \{c_1, c_2, \ldots, c_j\}$. Calculate the attention generating weight vector V and weighted representation F':

$$c_j = \max f(j), \tag{5}$$

$$V = \mathrm{softmax}(c), \tag{6}$$

$$F' = V \odot F. \tag{7}$$

The DCNN was trained in Python with Keras, using the operating system of deepin 15.11. The network training was sped up by a parallel deep-learning platform built with CUDA9.0+cuDNN7.1 and NVIDIA GeForce GTX 1080 Ti, which enables hardware acceleration. A total of 300 rounds of training were carried out, each of which has a batch size (Batch-Size) of 500. The sklearn train-test-split toolkit was called to automatically divide the dataset into a training set and a test set by the ratio of 9:1. The error was measured by mean absolute error (MAE), i.e., the average error between predicted and true values. The errors of our network on the training set and test set are shown in Figure 5a. After 50 rounds of training, the errors fluctuated less violently, and the mean error could then be reduced to 0.02. After 300 rounds of training, the error was maintained at 0.008. To prevent overfitting, the dropout layer was added to enhance the robustness of the DCNN prediction. The prediction accuracy of the network stabilized at nearly 91% after 50 rounds, as shown in Figure 5b.

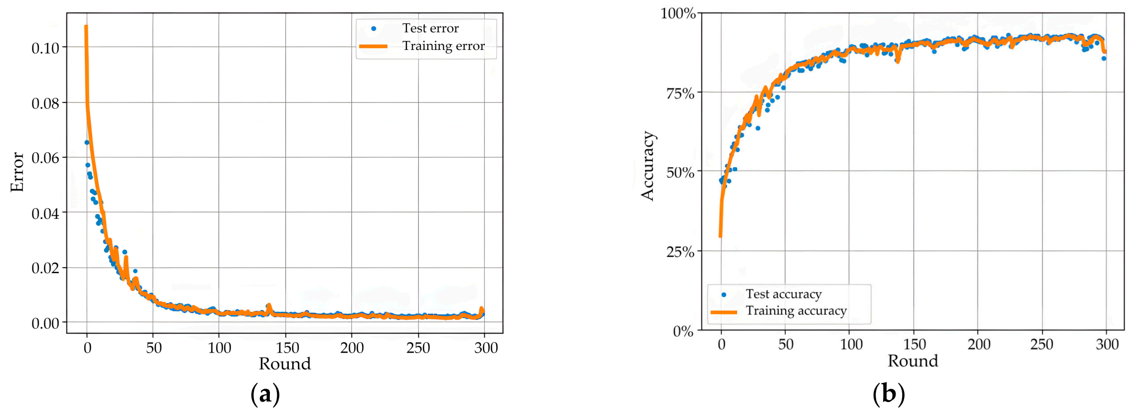

Figure 5. Training error and training accuracy of the DCNN: (**a**) DCNN's training error; and (**b**) DCNN's training accuracy.

Figure 6 compares the prediction MAE of our DCNN with that of traditional machine-learning tools such as support vector machine (SVM), logistic regression (LR), k-nearest neighbors (KNN), and decision tree (DT). The comparison shows that the DCNN still has errors between the predicted and true values for the six kinds of air pollutants, namely, CO_2, CO, SO_X, NO_X, PM, and CH_4. However, the errors are within the allowable range, and the DCNN achieves more accurate predictions than the contrastive methods.

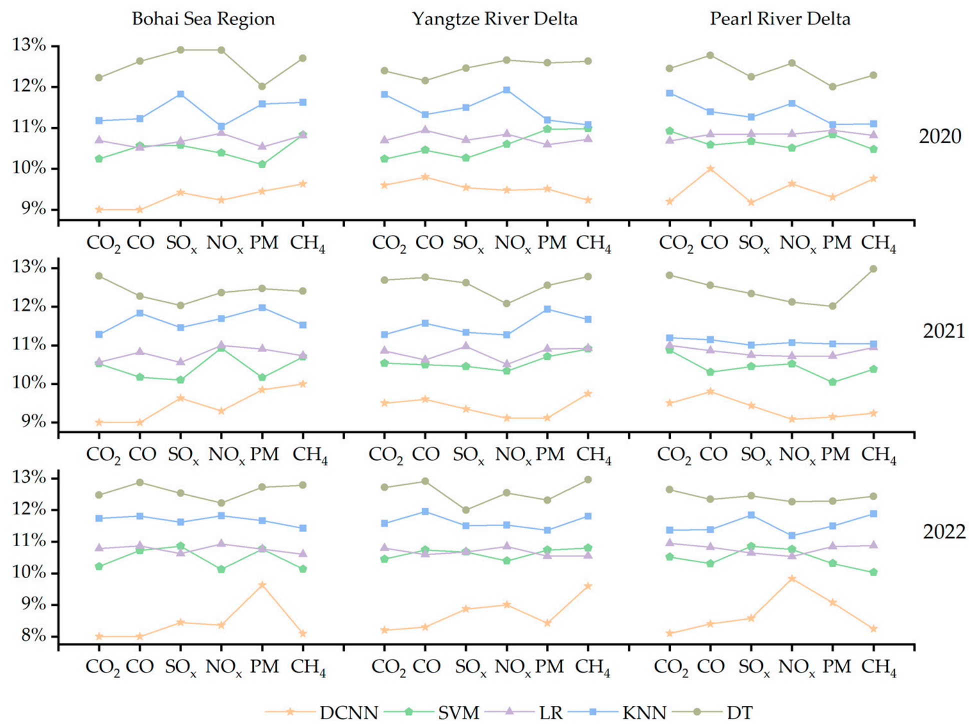

Figure 6. Prediction MAEs of different methods.

3.5. System Test

Following the above method, real system tests were conducted for two of the selected sea areas, namely, the Bay of Bengal in India and the eastern coast of China, plus three additional sea areas, i.e., the Arabian Sea, the Mediterranean, and the Caribbean Sea. Figure 7 shows the air pollutant emissions from ships in these sea areas for the entire year of 2022, calculated by the weight units in each km^2. According to the results on the Bay of Bengal in India, the air pollutant emissions from ships are severe in the Strait of Malacca in Singapore. In the eastern coastal region of China, the air pollutants emitted by ships have a high concentration in the sea near the Bohai Bay and Shanghai. In the Arabian Sea, the air pollutant emissions from ships mainly converge in several waterways of the Middle East, including Dubai, the Bab-el-Mandeb Strait, and the Gulf of Aden. In the Mediterranean, the air pollutant emissions from ships are unoptimistic in the Aegean Sea and the waters surrounding Italy. The Caribbean Sea is the least affected by air pollutants emitted from ships in the above regions, with only Cuba, Jamaica, and Haiti facing a certain degree of air pollution.

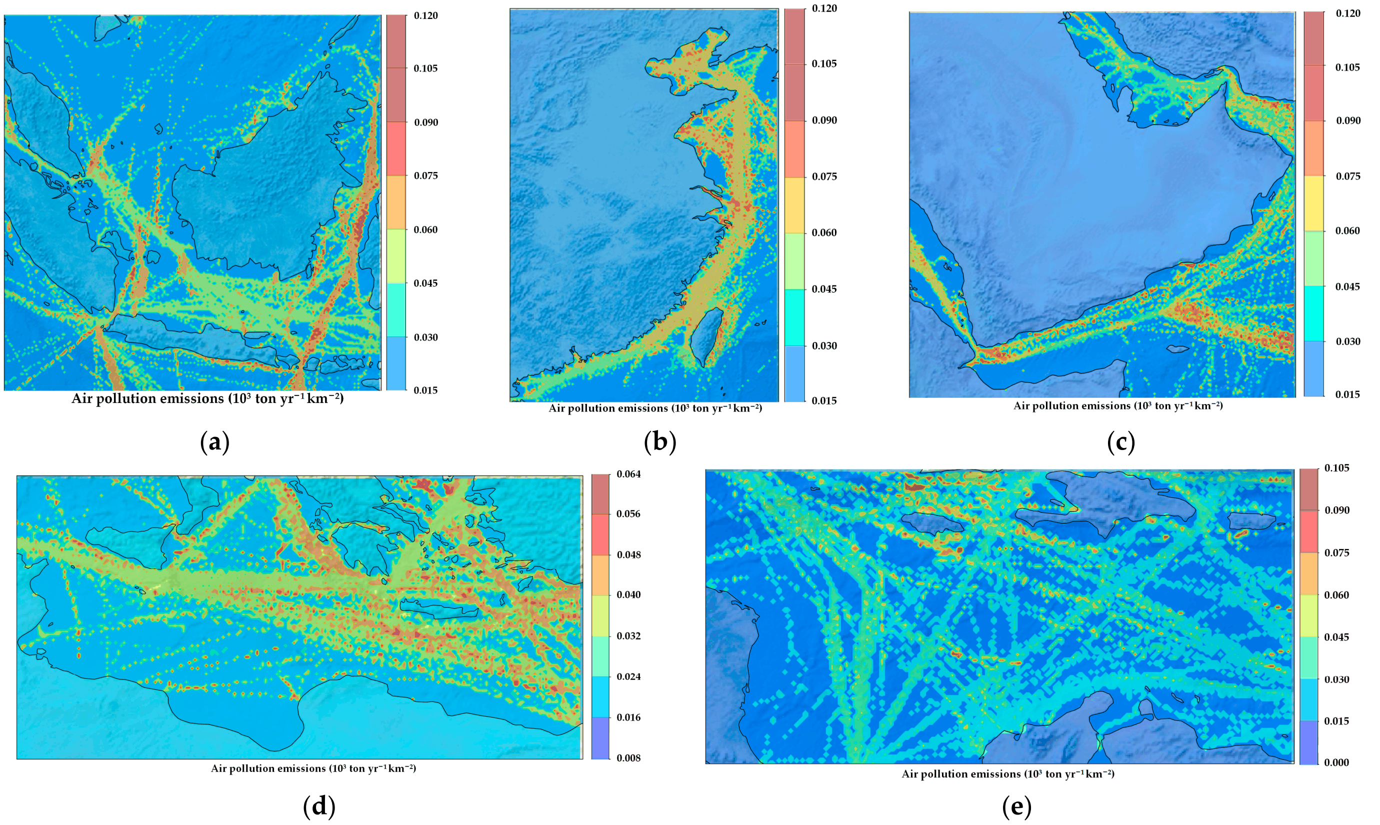

Figure 7. System test results: (**a**) Bay of Bengal in India; (**b**) eastern coast of China; (**c**) Arabian Sea; (**d**) Mediterranean; and (**e**) Caribbean Sea.

4. Platform-Based Interactive Teaching

Based on big data analysis, artificial intelligence, and virtual reality, our experimental platform for green shipping monitoring can monitor the dynamics and check the statistics of 147,000 registered ships, which belong to more than 10 types, and up to six air pollutants around the world. The interactive teaching based on the experimental platform helps students to form a holistic understanding of air pollutant emissions in marine transportation, and the emission control of the global supply chain, such that they can intuitively experience different types of ships and their air pollutant emissions across the globe. In addition, experimental learning can be flexibly arranged according to the needs of course teaching. Through flexible learning, students can master the dynamic monitoring model of air pollutant emissions from ships, grasp relevant accounting and statistical methods, and familiarize themselves with the control strategies for air pollutants emitted from ships.

4.1. Teaching Contents

4.1.1. Experimental Software

We offered students two ways of learning. First, genuine tools of the geographical information system (GIS), namely, ArcGIS and MapInfo, programming languages such as Python, MATLAB, or R, and Excel were installed on personal computers. Second, our experimental platform for green shipping monitoring includes the platform server, display terminal, control terminal, etc.

4.1.2. Experimental Methods

Method 1: Processing ship AIS data, aerosol data, and marine meteorological data. Students are expected to understand the meaning of each field in dynamic and static AIS data, aerosol data, and marine meteorological data; become familiar with the transmission frequency of data from different sources; understand the sources of all fields in the original data; identify the causes of missing and defected fields; clarify the different formats of the same semantic field; and master the conversion technique for each format.

Method 2: Modeling principle for dynamic monitoring of air pollutants emitted from ships. Students are expected to understand the integration, preprocessing, correlation analysis, and dynamic estimation of ship AIS data, aerosol data, and marine meteorological data in the designated area, and know the principle for the dynamic monitoring of ship air pollutant emissions. They also need to learn the complex relationship between ship activities, navigation environment, and air pollutant emissions.

Method 3: Visualizing ship position, route, port, sea area, and other objects. Students are expected to identify routes based on the dynamic trajectories in ship AIS data; recognize and define the boundaries of major ports and sea areas, in the light of the major shipping areas around the world; and learn to visualize ship position, route, port, sea area, and other objects, using GIS tools.

Method 4: Accounting, statistical processing, and analysis of ship air pollutant emissions. Students are expected to realize the online monitoring, display, and query of air pollutant emissions from ships; and carry out accounting, statistical processing, and analysis of the AIS data and air pollutant trajectories of any ship from the angles of the classes of port, sea area, ship, tonnage, pollutant, time, cargo, cargo flow, etc.

Method 5: Assessing the implementation effect of the emission control area (ECA) policy, and the control strategy of ship air pollutant emissions. Students are expected to assess the implementation effect of the ECA policy, and use the heat map to illustrate the distribution of air pollutants emitted from ships in the ECA. In addition, they should be able to discuss the prewarning scheme for ship air pollutant emissions in specific areas, such as ports and sea areas, and understand the impact of changes in ECA boundaries and standards.

4.2. Teaching Method

4.2.1. Implementation Process

The case study approach was adopted in our teaching scheme. Under the guidance of the teacher, the students were divided into several groups to complete a case involving multiple experimental steps. The hands-on operation allows students to understand and master the above experimental principles.

Step 1: The students were split into several groups, each of which contains three to four people. Some original data from different sea areas with frequent shipping activities were distributed to these groups. This means the sea areas distributed to different groups have different boundaries. The groups vary in port, sea area, and ship data, aerosol data, and marine meteorological data.

Step 2: Based on the original data, ArcGIS or MapInfo, and Python, MATLAB, or R were employed to identify ship position and route, visualize the historical trajectories in the AIS data, and recognize the main ports and sea areas distributed to each group, before defining the boundaries of the sea areas.

Step 3: Each group screened the visualized ship position, route, port, sea area, and other objects, deleted abnormal data, and summarized the causes of the abnormalities. The common attributes of the three source datasets, namely, time, longitude, and latitude, were extracted and converted into a unified format.

Step 4: Time, longitude, and latitude were taken as primary keys to match multiple attributes of ship activities, navigation environment, and air pollutant emissions. The proposed DCNN was called to dynamically estimate ship air pollutant emissions, and output results in a fixed format.

Step 5: According to the classes of port, sea area, ship, tonnage, pollutant, time, cargo, and cargo flow, we accounted, statistically processed, and analyzed the results on ship air pollutant emissions, and illustrated the results in charts.

Step 6: The spatial analysis technology of GIS tools was employed to discretize the air pollutants emitted from ships, forming a heat map.

Step 7: Group discussion was organized to develop an ECA for the distributed sea areas according to the preset prewarning standard for ship air pollutant emissions, along with the boundaries and implementation standard of the ECA.

Step 8: A summary chart was prepared for each step of Steps 1–7, and an experimental report was formulated.

4.2.2. Interactive Operation

Through an on-site demonstration, the teacher explained the technical points in Steps 1–7 above. The students followed the explanations to operate on their personal computers, and thus learn the relevant knowledge points. Our experimental platform for green shipping monitoring requires students to master 10 interactive operations related to the accounting, statistical processing, and analysis of ship air pollutant emissions in the study case.

Operation 1: Visualization of ship position. The students are required to switch between global base maps; become familiar with charts, ports, ships, marine meteorology, and other signs; and learn the information associated with each icon. By clicking the icon of ship position, one can find the dynamic and static information of the associated AIS data.

Operation 2: Visualization of the route. This operation draws the historical AIS trajectories of specific ships (dry bulk carriers, oil tankers, container ships, etc.) within the specified time range, and exports the relevant data.

Operation 3: Visualization of air pollutant emissions from ships. This operation dynamically estimates the air pollutant emissions of ships in the designated area, forms the changing trend based on the time series, and exports the relevant data.

Operation 4: Visualization of emissions by port and sea area. This operation summarizes the air pollutants emitted from ships in different ports and sea areas, and sorts ports and sea areas by the emission magnitude.

Operation 5: Visualization of emissions by ship type. Based on ship types, this operation accounts and statistically processes the air pollutants emitted by various types of ships in the designated area, and analyzes the difference between ship types in air pollutant emissions.

Operation 6: Visualization of emissions by tonnage. Based on ship types, this operation further accounts and statistically processes the air pollutants emitted by main types of ships of different tonnages, and analyzes the relevance between tonnage and air pollutant emissions.

Operation 7: Visualization of emissions by registry. According to the flag state where the ship is registered, this operation calculates the air pollutants emitted from the ship in the designated area, and analyzes the difference between ship registries in air pollutant emissions.

Operation 8: Analysis by pollutant. This operation statistically processes each of the six types of air pollutants emitted by ships, such as CO_2, CO, SO_X, NO_X, PM, and CH_4, revealing the magnitude difference of air pollutants in concentration.

Operation 9: Simulation of ECA policy implementation. According to the different settings of ECA boundaries (such as 12, 50, 100, and 200 nautical miles) and standards (such as $SO_X \leq 0.1\%$ m/m, and $SO_X \leq 0.5\%$ m/m), this operation draws the corresponding heat maps for ship air pollutant emissions [30].

Operation 10: Simulation of the control effect of ship air pollutant emissions. This operation sets the proportion of installed emission reduction technology based on ship types and tonnages in different sea areas, and plots the corresponding heat maps for ship air pollutant emissions [31].

5. Appraisal of Learning Effect

Currently, our university offers the following courses related to shipping, greenness, environment, and sustainability: postgraduate courses such as Green Shipping Economics and Computational Mathematics, and undergraduate courses such as Green Supply Chain Management and Practice and Shipping Supply Chain Operation Management. Our experiment covered 492 students who chose these courses, including 262 undergraduate students and 230 postgraduate students. We evaluated the integration of practical teaching and the effect of experimental learning from two aspects: the students' basic abilities after teaching; and their participation, performance, and feelings during teaching.

5.1. Comparative Analysis of Students' Basic Abilities

After completing experimental courses, the basic abilities of the students directly reflect their learning state. We customized a batch of complete datasets of "ship AIS–marine meteorology–sea air pollution" for each group, and surveyed how well the students recognize different datasets, understand the correlations between data attributes, and master interactive operations 1–10 before and after the experimental learning.

5.1.1. Cognition of Datasets

Figure 8 compares the students' cognition of datasets. Through experimental learning, the students' cognition of the three datasets was improved to varying degrees. The improvement was more significant among undergraduate students than postgraduate students, and more remarkable over marine meteorology and sea air pollution than over ship AIS. In particular, the students made prominent progress in the cognition of NC, EC, wave height, and AOD. This means postgraduates students are more familiar with data science than undergraduate students, and ship AIS data are widely taught in the daily courses of our students. Further, the students grasped the common attributes of the three datasets (time, longitude, and latitude) very accurately.

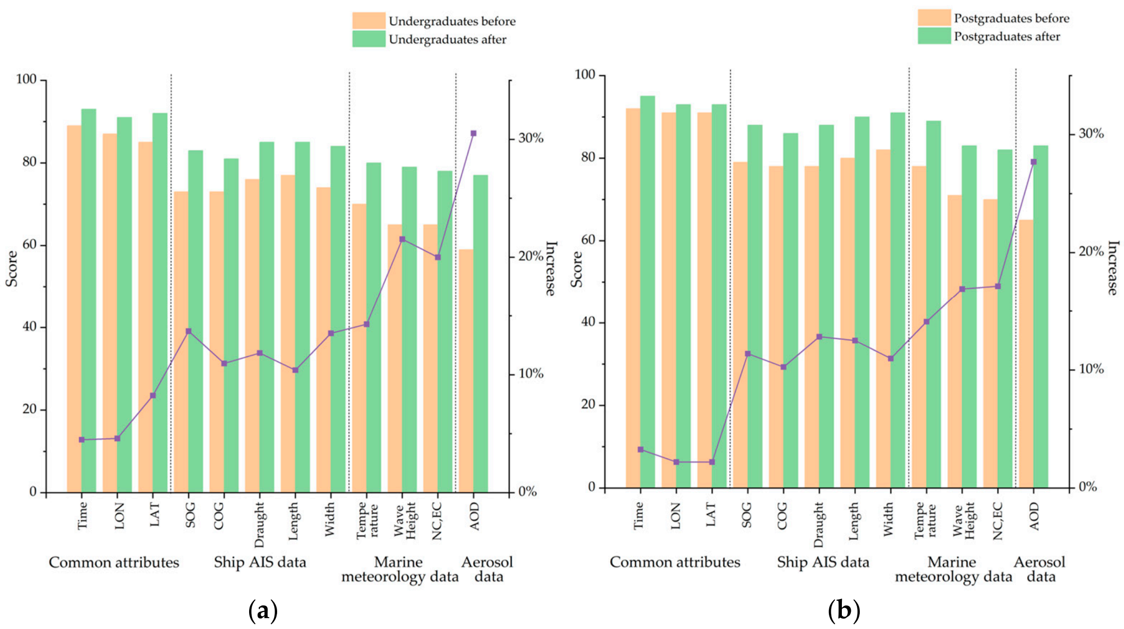

Figure 8. Students' cognition of the three datasets: (**a**) undergraduate students' cognition; and (**b**) postgraduate students' cognition.

5.1.2. Understanding of Data Correlations

As shown in Figure 9, the students understood the basics of the three datasets, and perceived the exact correlations between sea air pollution and the data attributes of speed, NC, EC, displacement, water temperature, and wave height. Through experimental learning, the students generally observed the nonlinear correlations between sea air pollution and attributes such as time, SOG, NC, EC, displacement (ship length, ship width, and draught depth), water temperature, and wave height. The observations had some differences arising from the varied ranges of selected areas and time. Both undergraduates and postgraduates understood the relevant information much more profoundly than before. Previously, they only perceived the simple correlations or linear relationship between AOD and the said attributes.

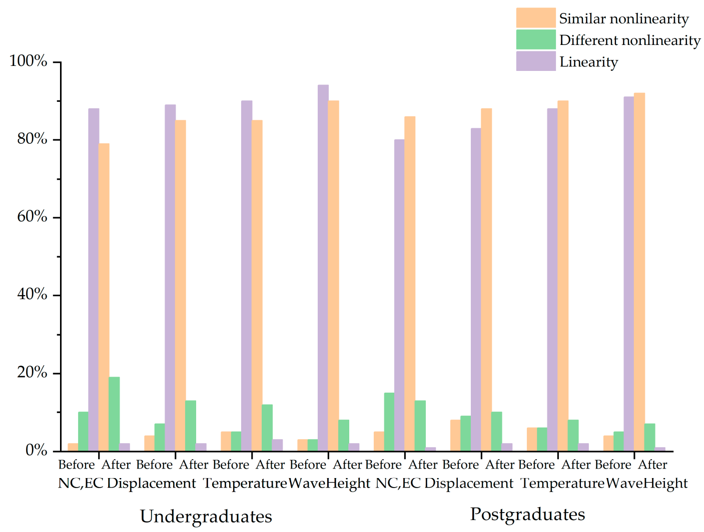

Figure 9. Students' understanding of data correlations.

5.1.3. Mastery of Interactive Operations

Through experimental learning, the students deeply understood the data related to shipping activities, navigation environment, and air pollutant emissions. The learning appraisal results of the 10 interactive operations are displayed in Figure 10. It can be observed that the students failed to recognize the accounting, statistical processing, and analysis of ship air pollutant emissions systematically, before the experimental learning. Through a series of visual and simulation operations, the students had a deep understanding of the green shipping monitoring indices, and learned how to utilize multiple statistical indices, such as port and sea area, ship type, ship tonnage, and ship registry. Moreover, the students now understood the principle and effect of related tools. Before the experimental learning, they merely knew the concepts of the implementation effect assessment of the ECA policy and emission control strategies for ship air pollutants.

5.2. Comparative Analysis of Students' Participation, Performance, and Feelings

Experimental learning expects students to complete an experimental report through the case study, and attaches importance to the appraisal of the acquired skills, highlighting the significance of active participation and interaction in the learning process. The students could have intuitive feelings in the green shipping monitoring scene reproduced by virtual reality. Here, we investigated the students' academic performance, experimental participation, individual thinking stimulation, and satisfaction with teaching quality.

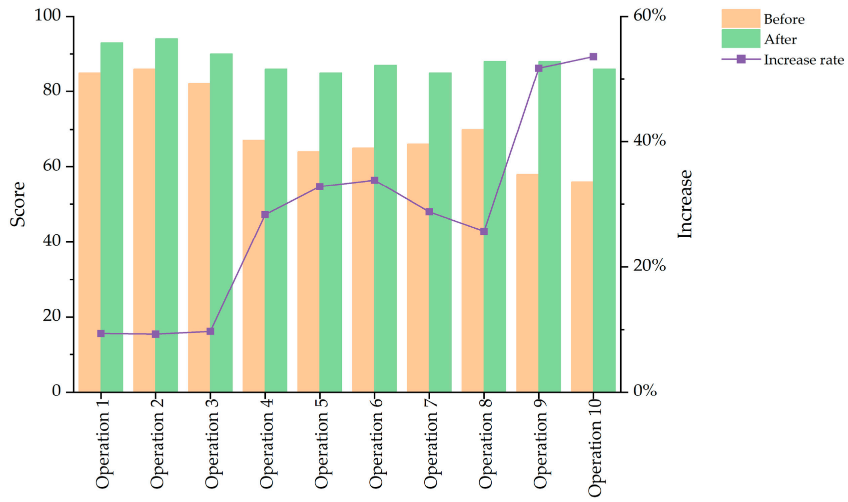

Figure 10. Students' mastery of 10 interactive operations.

5.2.1. Academic Performance

The contents of experimental learning have overlapping knowledge points with the selected courses. Figure 11 compares the students' scores on these knowledge points. Through experimental learning, the students understood the knowledge points in the original curriculum more clearly, performed well on the indirect related knowledge points, and achieved an improvement of overall performance. Thus, experimental learning effectively supports students' learning and cognition via digital and exploratory learning.

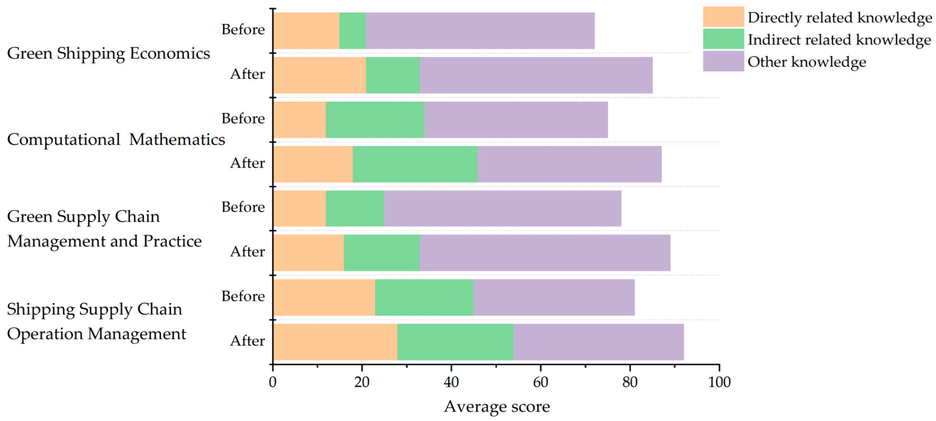

Figure 11. Students' academic performance. The dotted line is to distinguish the academic performance before and after the experimental learning of each course.

5.2.2. Experimental Participation

In experimental learning, the teacher and students must participate simultaneously to realize the objective of practical teaching. Figure 12 reports the students' experimental participation. Firstly, the students were active about experimental learning, and heavily involved in the experiment. Postgraduate students performed better in the autonomous completion of learning tasks (with no guidance throughout the learning) than undergraduate students. Second, all students could come up with a chart of the overall flow. On the whole, most students manifested strong knowledge-building abilities.

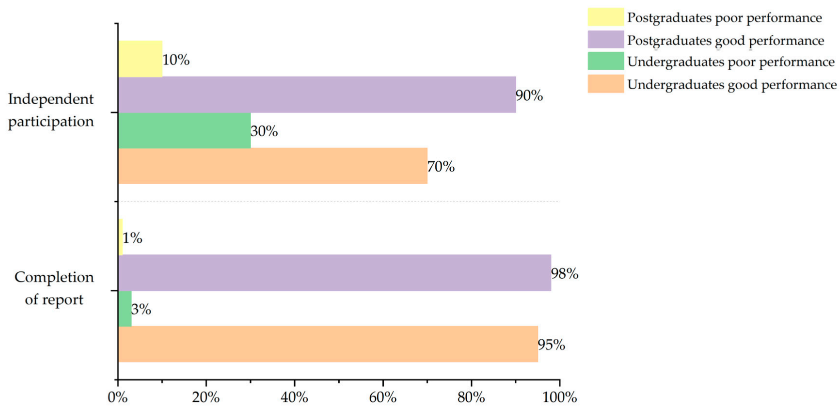

Figure 12. Students' experimental participation. The dotted line is to distinguish the two indicators of experimental participation.

5.2.3. Stimulation of Individual Thinking

We also checked whether experimental learning stimulated the individual thinking of the students. According to the results in Figure 13, about 54% of the students believed that experimental teaching effectively promoted their active thinking; about 33% said experimental teaching often stimulated their thinking; about 10% reported a general effect of experimental teaching in stimulating individual thinking; and only 3% did not perceive any such effect. Overall, our teaching approach, featured by "independence, exploration, and co-operation", helps to simulate students' initiative, enthusiasm, and creativity.

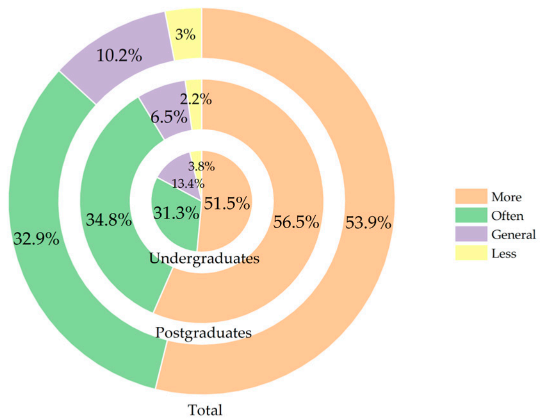

Figure 13. Stimulation of individual thinking.

5.2.4. Satisfaction with Experimental Teaching Quality

Figure 14 reports the survey results on student satisfaction with experimental teaching quality. Overall, the novel teaching contents, intelligent technical support, and pleasant learning experience received the best evaluations, and were among the highest-rated indices of experimental teaching quality. In terms of teaching contents, the students were most satisfied with the fact that the teaching contents do not intend to be all-inclusive, but encourage deep understanding, and try to integrate multi-dimensional knowledge. In terms of technical support, the students were most satisfied with good peer support and better task orientation in the teaching process.

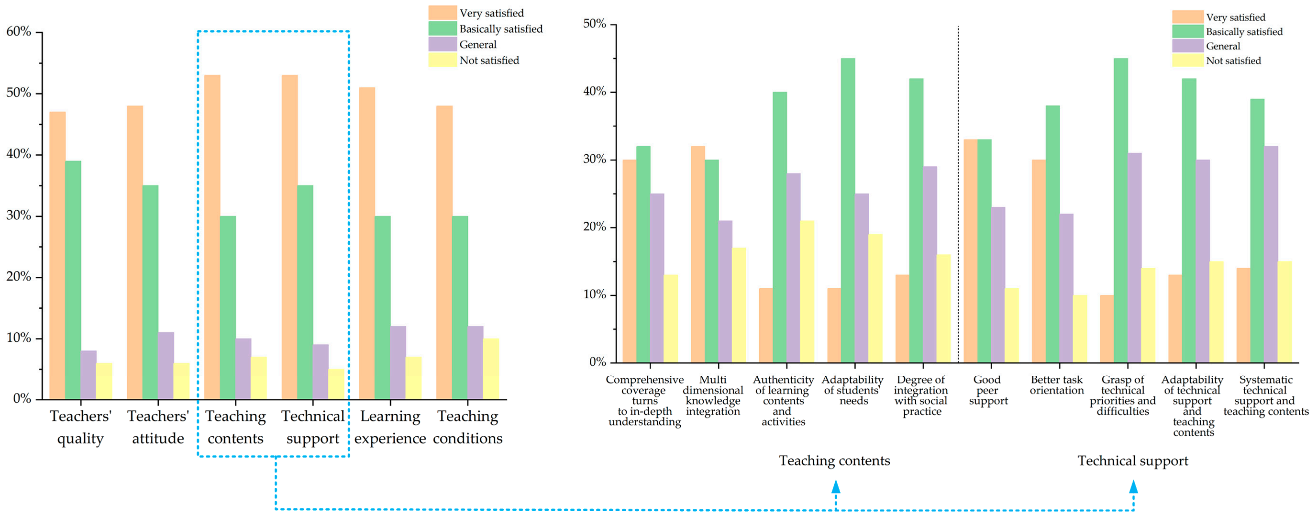

Figure 14. Satisfaction with experimental teaching quality. The dotted line is to distinguish between teaching content and technical support.

6. Conclusions

In the context of NBS construction and the advancement of big data technology, the main goal of teaching reform is to cultivate well-rounded talents with data intelligence through a student-centered approach. Through the collaboration between the university and enterprises, we successfully established a green shipping monitoring experimental platform based on big data technology, and systematically tested its accuracy in the dynamic monitoring of air pollutant emissions from ships. Subsequently, we proposed interactive teaching content and methods based on the experimental platform. After that, we investigated the learning effect of this experimental platform. The results show that: Firstly, the students had a deeper understanding of the original data and recognized the correlations between data attributes, which promote the mastery of the cross-cutting knowledge points in the original curriculum. Moreover, the learning of interactive operations promotes the students' knowledge application, and broaden their horizon in practical teaching. Secondly, experimental learning boosts the students' academic performance, classroom participation, and individual thinking. According to the survey results on students' satisfaction with the quality of experimental teaching, the teaching quality could be effectively improved through intelligent technical support, task-driven activities, a multi-dimensional process, and personalized guidance. In this way, the students could do better in solving problems, and realize innovation in practice. The expertise gained from our platform-construction endeavors and the practical teaching model we have developed can be extended to other disciplines, such as maritime management and intelligent transportation, providing new ideas and methods for practical teaching in these fields. The experimental teaching approach we have designed seamlessly integrates with real-world applications, ranging from data cognition and basic operations to decision analysis. It helps to nurture well-rounded maritime talents with data intelligence, equipping them with the essential knowledge and skills demanded in the field.

The big-data-based experimental platform for green shipping monitoring could be improved by collecting better datasets. It is necessary to expand the size and dimensionality of data on the process and elements of air pollutant emissions in maritime transport, and the joint pre-warning of emission governance in the global supply chain system. The multi-source heterogeneous data need to be fused and mined to provide new teaching platforms with key materials. In the next step, it is important to further enhance the quality of practical teaching, and improve teaching methods, using intelligent teaching elements, in a bid to develop and disseminate teaching plans that explain profound knowledge in simple terms.

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