

A Practice-Based Study of the Digital and Intelligent Upgrading of a Big Data Technology Specialty Cluster

Jun Zhang, Taizhi Lv *

School of Information Engineering, Jiangsu Maritime Institute, Nanjing, Jiangsu, 211170, China

* Corresponding author: Taizhi Lv (Email: lvtazhi@163.com)

Abstract: The growing integration of artificial intelligence into shipping is reshaping the occupations served by big data technology specialty clusters, bringing together data processing, intelligent analysis, and industry applications. To address gaps between AI competency development and occupational tasks, weak connections between curricula and industry scenarios, and insufficient support for faculty capabilities and teaching resources, this study combines literature analysis with a case study of Jiangsu Maritime Institute to examine how AI can be integrated into specialty cluster development. The practice restructures competencies around typical smart shipping tasks, establishes a three-tier curriculum progressing from digital and AI literacy to AI algorithms and scenario-based applications and then to integrated industry innovation, and develops faculty AI application and instructional design capabilities through the Three Engagements initiative. Human–AI collaboration is explored in lesson preparation, instruction, assessment, and teaching management. The study argues that upgrading should connect AI learning, industry task practice, and instructional improvement. Scenario-based design, task restructuring, differentiated implementation, and continuous assessment can support students in developing the ability to apply digital and intelligent technologies in smart shipping.

Keywords: Big Data Technology Specialty Cluster; AI Empowerment; Digital and Intelligent Upgrading; Smart Shipping; Curriculum Reform.

1. Introduction

Artificial intelligence is changing how shipping information systems process data and support business operations. Vessel monitoring, port scheduling, energy efficiency management, and water pollution regulation are moving beyond data recording and statistical reporting toward intelligent recognition, predictive analysis, and decision support. Relevant occupations require practitioners to master data collection, governance, and development, understand the conditions under which AI methods are applicable, and apply models, verify results, and integrate systems within shipping operations. Higher vocational big data technology specialty clusters therefore need coordinated changes in their training objectives, curriculum content, and instructional organisation. The Opinions on Accelerating Education Digitalisation, issued by the Ministry of Education and eight other departments, call for AI to support educational transformation [1]. The AI Plus Education Action Plan further calls for the intelligent upgrading of traditional vocational provision and the systematic design of AI-integrated programmes, curricula, and teaching systems [2]. These policies indicate that AI integration into specialty cluster development must be translated into occupational competencies, course tasks, and teaching processes in ways that reflect the practical orientation of vocational education.

Research in China initially focused on the role of AI in the overall transformation of vocational education. Chen et al. examine its underlying logic, practical challenges, and development pathways, emphasising innovation in teaching practices and the ethical regulation of technology [3]. Cai et al. discuss AI empowerment in terms of training objectives, learning content, instructional processes, educational mechanisms, and assessment, and propose intelligent learning environments, curriculum optimisation, and faculty

development [4]. These studies suggest that AI applications require coordinated changes across the elements of talent development. Research has also increasingly addressed faculty roles and AI capabilities. Wang Gang et al. discuss how AI reshapes the roles of higher vocational teachers and stress the need to preserve teacher agency and educational responsibility [5]. Li et al. analyse vocational teachers' AI teaching competencies in terms of educational principles, social responsibility, knowledge and skills, instructional applications, occupational competencies, and professional development [6]. These findings inform faculty training and suggest that AI competence extends beyond proficiency in operating tools to include professional judgement, task design, and learning guidance. Existing research has thus progressed from general discussions of value to curricula, teachers, and instructional applications. However, for big data technology specialty clusters with a strong industry focus, several practical questions remain: how general AI technologies can become competencies for shipping data processing occupations; how data-related and AI-related courses can be connected; how industry projects can be adapted for higher vocational students; and how intelligent tools can enter the classroom without weakening foundational skills training. Examining these practices can make AI integration into specialty cluster development more actionable.

Focusing on smart shipping applications, this study examines the digital and intelligent upgrading of a big data technology specialty cluster. Drawing on Chinese research on AI empowerment in vocational education, it reviews practices in competency restructuring, curriculum reform, faculty development, resource translation, and instructional implementation. Particular attention is given to how AI becomes part of specialty cluster content, supports authentic task-based practice, and improves teaching and learning.

2. Challenges in Integrating AI into Specialty Cluster Development

2.1. Gaps between Training Objectives and Intelligent Occupational Tasks

Big data technology specialty clusters emphasise data collection, processing, and development, whereas smart shipping occupations also require an understanding of operational indicators, the selection of analytical methods, and the verification of model outputs. When training objectives remain centred on isolated technical skills, students may be able to process data without understanding its purpose or run models without being able to assess their results. Upgrading must therefore translate AI competencies into occupational tasks and specify what students should be able to do in particular scenarios.

2.2. Limited Continuity between Course Knowledge and Industry Applications

If AI content is introduced only through additional courses or a small number of examples, it can remain separate from existing courses in databases, programming, and data governance. Students then encounter disconnected datasets and tasks across courses and struggle to gain experience of complete projects. Using a shipping scenario merely to introduce a course is also insufficient for developing business understanding and engineering skills. Such scenarios need to become connected sequences of tasks spanning data acquisition, model application, and interpretation of results.

2.3. Insufficient Support for Faculty Capabilities and Resource Renewal

AI technologies evolve rapidly, while industry data are highly domain-specific. Teachers must understand algorithms, work with operational data, interface specifications, and business constraints, and then adapt complete engineering projects into learning tasks appropriate for students. Meanwhile, project datasets, models, and technical documentation are unlikely to become shared teaching resources unless they are organised, authorised for use, and maintained. Faculty development and resource renewal therefore require stable collaborative arrangements.

3. Practices for the Digital and Intelligent Upgrading of the Specialty Cluster

3.1. Restructuring Competencies around Occupational Tasks

The specialty cluster uses the development of AI technology applications as a driver to move big data-related provision beyond general technical learning toward an integration of data capabilities, AI applications, and an understanding of shipping operations. The starting point is to analyse actual work in smart shipping and identify the respective tasks and shared foundations of the programmes involved. For example, vessel energy efficiency monitoring involves operational data collection and analysis, vessel recognition involves computer vision models, and intelligent shipping question answering involves the organisation of domain knowledge and natural language processing. Although the technical emphasis varies, all these tasks depend

on data quality, business understanding, and result verification.

Accordingly, the competency structure is organised into foundational competencies, scenario application competencies, and integrated practical competencies. Foundational competencies include programming, data organisation, basic AI literacy, and knowledge of shipping operations. Scenario application competencies include data governance, algorithm use, model training, performance analysis, and visual communication. Integrated practical competencies include requirements analysis, systems integration, testing and validation, teamwork, and the explanation of proposed solutions. Clearly defined competency levels allow courses within the cluster to contribute to common objectives while reducing duplication and gaps.

In implementation, course objectives are mapped to occupational tasks. An objective such as mastering an algorithm is translated into the ability to select a method for a particular dataset, validate its performance, and explain the results. Data engineering pathways emphasise high-quality data provision and model interface applications, while AI application pathways emphasise model selection, error analysis, and fitness for operational needs. Shared foundations, differentiated pathways, and collaboration on integrated projects connect AI with the cluster's existing competencies.

3.2. Developing AI Competencies through a Three-Tier Curriculum

Following the rationale for organising the specialty cluster, the curriculum uses AI as its technological thread and project tasks as learning vehicles. As shown in Figure 1, it progresses through three tiers: digital and AI literacy at the foundational level, AI algorithms and engineering applications at the intermediate level, and industry-oriented intelligent decision-making and innovation at the advanced level. Talent development is restructured by linking industry value chains, application scenarios, work tasks, courses, and competencies, enabling closer integration between AI technologies and shipping operations.

The foundational tier combines digital and AI literacy with cross-domain understanding. Introduction to Artificial Intelligence, Introduction to Navigation, and Introduction to Smart Shipping are connected with Python Programming and Data Structures. AI literacy teaching helps students understand the relationships among data, algorithms, and models, recognise the problems AI can address, identify the conditions required, and assess outputs. Shipping-related courses provide basic knowledge of vessels, ports, and regulatory operations so that students can understand data sources and indicators in subsequent projects.

The advanced tier draws on the Smart Shipping Innovation Workshop to involve students in integrated tasks such as shipping data governance, model optimisation, intelligent sensing development, and decision support. Teachers assign roles in data verification, sample annotation, model debugging, interface development, and testing according to students' preparation, gradually increasing task complexity. Students submit working outputs and explain requirements, method selection, and test results, extending course learning into complete engineering practice.



Figure 1. Three-tier Architecture Curriculum System

The three tiers emphasise gradual progression. General education develops understanding, scenario modules train methods, and integrated projects develop collaborative application capabilities. Students who are not yet ready for complete development projects first undertake clearly bounded and verifiable subtasks before joining cross-course collaboration. This provides meaningful participation opportunities for students with different starting points.

3.3. Restructuring AI Learning Tasks through Authentic Projects

Bringing industry projects into teaching requires selection, decomposition, adaptation, and assessment design. Drawing on vessel energy efficiency monitoring, intelligent shore power applications, joint water pollution regulation, and intelligent shipping question answering, the specialty cluster selects tasks that represent occupational competencies and can be completed within course schedules. This creates a learning process from operational context to technical implementation. Projects are selected for their technical relevance and for whether students can access the necessary data, perform the required operations, and assess the results.

First, operational problems and key constraints are retained. A task brief should identify the users, the problem to be solved, the input data, and the operational stage at which the output will be used. For example, a vessel recognition task should provide images together with the recognition targets, contextual conditions, and potential consequences of false detections. An energy efficiency analysis task should explain operating conditions and business indicators so that students do more than produce outputs from code templates.

Second, complete engineering projects are decomposed into sequential learning tasks. A recognition project may progress through sample familiarisation, annotation verification, baseline model execution, parameter adjustment, error analysis, and result presentation. Students with weaker foundations complete data and baseline tasks, while more advanced students proceed to optimisation and systems integration. Each stage specifies inputs, operational requirements, and deliverables, allowing complexity to increase as learning progresses.

Third, algorithm comparison and result interpretation are incorporated into practice. After running a model, students compare the performance of different methods or parameter settings, analyse misclassified samples, and explain whether the results meet operational requirements. An energy efficiency task can begin with a statistical baseline before introducing machine learning, helping students understand why AI is used. Question-answering tasks require students to check knowledge sources and the evidence supporting answers, developing verification habits.

Finally, project outputs are used to check competency attainment. Assessment considers whether the system runs, whether data processing is appropriate, whether method selection is justified, whether testing is sufficient, and whether students can explain key code and operational results. These task decomposition principles summarise how the case projects can be adapted for teaching. They can be combined flexibly according to students' preparation and available resources, avoiding the wholesale replication of production systems beyond students' capabilities.

3.4. Developing Faculty AI Application Capabilities through the Three Engagements Initiative

As shown in figure 2, the specialty cluster establishes ongoing practical development opportunities through faculty engagement with research institutes, enterprises, and workshops. These Three Engagements connect technological learning, industry applications, and instructional design. Faculty development aligns with the emphasis on digital literacy and integrated AI applications in the Ministry of Education General Office's Notice on Implementing the Action for Digitally Empowered Teacher Development [7], and translates these requirements into shipping-related courses and projects.



Figure 2. The Capacity improvement of teachers for the "Three Engagements Initiative"

Engagement with research institutes focuses on understanding technical methods. Through collaboration with relevant universities and research organisations, teachers learn and test methods for shipping data governance, intelligent recognition, and predictive analysis. Learning outcomes should be translated into explanations of principles, experimental cases, and model demonstrations suitable for courses, enabling technological developments to enter teaching. Faculty learning should be assessed in terms of the ability to explain applicability, limitations, and instructional uses.

Engagement with enterprises focuses on engineering and operational constraints. Teachers participate in system development, data processing, and application testing in shipping enterprises, gaining an understanding of data quality, interface specifications, deployment environments, and delivery requirements. By documenting typical problems and how they are resolved, teachers develop operational cases, fault examples, and testing tasks for classroom use. Enterprise practice is thereby linked directly to curriculum renewal.

Engagement with workshops focuses on converting technical experience into instructional design. Teachers and engineers jointly guide students, divide complete projects into differentiated tasks, and refine task briefs, case descriptions, and assessment criteria during implementation. For a given project, specialty cluster teachers connect knowledge with tasks, enterprise engineers contribute operational requirements, and course teams jointly review difficulty,

workload, and assessment criteria so that students can complete authentic tasks with guidance.

Teachers should also learn to use intelligent tools appropriately. AI can assist with organising cases, generating test data, analysing common errors, and drafting feedback, while human review determines the final instructional content. Faculty training should be organised around concrete tasks, such as designing a scenario-based lesson, delivering project-based practice, and producing assessment feedback. This enables training outcomes to return directly to the classroom while preserving teachers' final judgement over content and assessment.

3.5. Human–AI Collaboration across the Teaching Process

During lesson preparation, teachers select project resources according to course objectives and students' prior knowledge. Intelligent tools can help organise operational background information, generate problem scenarios, and draft differentiated tasks, after which teachers review accuracy, difficulty, and feasibility. The essential questions are which competencies students should develop and which tasks and evidence will demonstrate them, ensuring that tool use serves instructional objectives.

During instruction, explanations of operations, model demonstrations, and student practice are combined. Teachers explain the problem and data, demonstrate key procedures, and then organise processing, training, and testing activities. Intelligent tools can explain code or offer operational prompts, while teachers develop students' judgement through questioning, debugging guidance, and comparison of results. When a model produces unexpected outputs, students should be guided to examine data, parameters, and operational assumptions in turn, turning errors into learning resources.

During assessment, process records are considered alongside final outputs. Data tasks focus on quality checks and processing rationale; model tasks focus on validation methods and error interpretation; integrated projects focus on usability, operational fitness, and collaboration. When generative AI has been used, code explanations, live modifications, and case reproduction can check students' understanding so that assessment reflects their actual capabilities.

During teaching management, task completion, common errors, and resource use are reviewed to adjust pacing, differentiated support, and resource allocation. Recurrent problems should first prompt a review of task instructions and prerequisite knowledge. Individual difficulties should receive targeted exercises and guidance. This establishes a cycle of identifying problems, analysing causes, adjusting tasks, and verifying improvements.

These stages distinguish between industry AI technologies and generative AI support tools. The former are used mainly for data analysis, visual recognition, and operational application training, while the latter support subsequent instructional refinement. AI offers suggestions and preliminary outputs; teachers remain responsible for instructional organisation and assessment, and students complete necessary independent operations and explain results. Human–AI collaboration thus develops alongside foundational skills training.

4. Conclusion

The digital and intelligent upgrading of big data technology specialty clusters should centre on AI integration and coordinate the adjustment of occupational competencies, curriculum restructuring, project task development, and instructional improvement. Focusing on smart shipping applications, Jiangsu Maritime Institute organises competency development through a three-tier curriculum, strengthens teachers' technological and operational understanding through the Three Engagements initiative, and explores human-AI collaboration in lesson preparation, instruction, assessment, and management. Together, these practices form an industry-oriented upgrading pathway.

At the core of this approach is the translation of AI technologies into occupational tasks that students can learn, perform, and explain, supported by teacher guidance, shared resources, and process assessment. Future development should refine task differentiation, resource maintenance, and the collection of learning evidence, while maintaining a stable connection between technological renewal and foundational skills training. This can bring specialty cluster development into closer alignment with smart shipping occupations and students' professional development.

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