

Constructing and Practicing an Industry-Education Integration Model for Big Data Graduate Programs Driven by Digital Intelligence

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Abstract: Amid the surge of digital intelligence, persistent gaps between theory and practice and the limited depth of university–industry collaboration have constrained the quality of graduate training in big data and its alignment with labor-market needs. This paper proposes an industry–education integration model tailored to the discipline, and articulates a theoretical framework for a tripartite collaboration among universities, enterprises, and technology. Grounded in digital-intelligent technologies, the framework aims to cultivate graduates’ three-dimensional capability profile-‘theory–technology–scenario’. The study not only offers a reproducible model for big data graduate education, but also positions industry–education integration as a ‘converter’ that smooths the transition from academia to industry, thereby supplying the digital economy with a cohort of professionals who combine academic depth with practical acuity.

Keywords: Digital Intelligence; Big Data Discipline; Industry-Education Integration; Graduate Training.

1. Introduction

In the current wave of global technological innovation and socio-economic transformation, digital-intelligentization (hereafter ‘digital intelligence’) has become an irresistible historical trend. Digital intelligence regards data as a primary factor of production; it harnesses artificial intelligence, machine learning, and other intelligent technologies to mine value from data, and employs such value to inform decisions and steer directions [1]. The process culminates in data-driven decision-making, intelligent process optimization, and human–machine collaborative innovation. It is characterized by three core features: (1) data-drivenness—data permeates every link and acts as the principal guide for decisions and behavior; (2) human–machine collaboration—effective coordination among humans and across systems; and (3) dynamic iteration—closed-loop feedback continuously refines intelligent models in an evolutionary cycle.

As digital intelligence deepens, big data graduate students must not only master foundational tasks such as data collection, cleaning, and storage, but also transcend the traditional boundaries of data processing to form a progressive ‘data–intelligence’ closed loop. Compared with conventional work centered on data mining, digital intelligence demands the tight coupling of data and algorithms. Accordingly, big data graduate students must shift from being ‘single-skill executors’ to ‘architects of digital-intelligence ecosystems’. [2]

2. Current Status of Big Data Graduate Training

At present, the disconnect between coursework and practice and the insufficient depth of university–industry collaboration is increasingly evident, hampering precise alignment between talent cultivation and industry demand.

2.1. Misalignment Between Coursework and Practice

Curricula still display a ‘theory-heavy, application-light’ bias [3]. Core courses focus primarily on foundational theory—data structures, algorithmic principles, and distributed computing—while offering limited coverage of the practical logic of the ‘data–intelligence’ loop in real industrial settings. For example, students who can deftly derive the mathematics of machine-learning algorithms often struggle to detect anomaly patterns in industrial sensor streams and to build predictive models. Although they may understand data-warehouse architectures, they lack hands-on experience in fusing multimodal data (e.g., text, images, and IoT time-series). On the practical side, training activities are frequently ‘simulated’ and ‘fragmented’: laboratory projects tend to rely on public datasets (e.g., MNIST, IMDb), which differ markedly from real enterprise data in noise, label completeness, and timeliness requirements. Practice under such ‘clean-data’ conditions leaves students ill-prepared for the ‘dirty data’ of production settings—leading to confusion in data cleaning and weak model deployment performance, and hindering the formation of a composite ‘data processing + intelligent modeling’ skill set.

This tendency toward theory over application persists: while courses cover topics such as data structures, algorithmic principles, and distributed systems, they rarely unpack in detail how the ‘data–intelligence’ closed loop operates in authentic industrial scenarios. As a result, students who can derive learning algorithms may be unable to determine whether anomalies exist in manufacturing sensor data and how to model them; and, despite instruction in data-warehouse design, they often lack methods for integrating multimodal inputs (text, images, IoT streams). Practical instruction likewise suffers from over-reading and fragmentation. In lab projects, public datasets like MNIST and IMDb are commonly used, yet they inadequately reflect operational realities such as noise, missing labels, and strict

latency constraints. Consequently, students train almost exclusively on ‘clean data’, whereas enterprises grapple with ‘dirty data’ in production. When thrust into real-world settings, students frequently do not know how to begin cleaning data, nor can they achieve robust model performance, falling short of the desired integration of ‘data processing + intelligent modeling’.

2.2. Insufficient Depth of University–Industry Cooperation

Most collaborations remain at a superficial level—short-term talks and case sharing—without deep, end-to-end co-design across the training lifecycle. For instance, when enterprises participate in course construction, they often contribute cases while university faculty still develop the content, leaving students without exposure to the business logic of digital-intelligence projects. During internships, confidentiality concerns lead enterprises to assign auxiliary tasks—data labeling or basic operations and maintenance—thus depriving students of experience with core work such as algorithm optimization and cross-domain data integration, and limiting opportunities to combine technical implementation with domain understanding. Resource matching also suffers from ‘misaligned needs’ and ‘disparate standards’: universities emphasize theoretical depth and novelty, while enterprises focus on practicality and business value. This divergence impedes sustained collaboration. A model that excels on academic metrics (e.g., accuracy) may ignore compute cost and deployment efficiency and thus fail to industrialize; conversely, enterprise transformation efforts falter without theoretical support and algorithmic innovation. Weak data-sharing mechanisms and imperfect benefit-sharing

frameworks further constrain collaboration depth. Enterprises, unwilling to risk core data leakage, hesitate to share real datasets; universities, constrained by evaluation systems that undervalue horizontal collaboration, lack incentives to push for deeper integration. The result is symbolic cooperation that rarely yields innovative, application-oriented talent suited to the digital-intelligence era.

Fundamentally, the current training model fails to adapt to the era’s ‘practice orientation’ and ‘cross-boundary integration’. Without effective pathways, we risk graduating students who can neither solve real industrial problems nor provide cross-disciplinary services for a digital-intelligence ecosystem—thus worsening the talent supply-demand mismatch.

3. Construction and Practice of an Industry–Education Integration–Based Teaching Model

Our work proceeds in two stages. First, we construct a digital-intelligence-oriented integration framework, clarify the core competency targets for big data majors, analyze how to build the curriculum system, teaching resources, collaboration mechanisms, and pedagogies under an integration paradigm, and develop a multi-dimensional evaluation system. Second, we study the application of ‘digital-intelligence’ technologies—big data, AI, cloud computing, service platforms, and IoT—in teaching, and build a digital-intelligence teaching platform. Through iterative practice, we distill insights into an innovative theory that, in turn, guides further practice, forming a closed-loop research cycle [4] (see Figure 1).

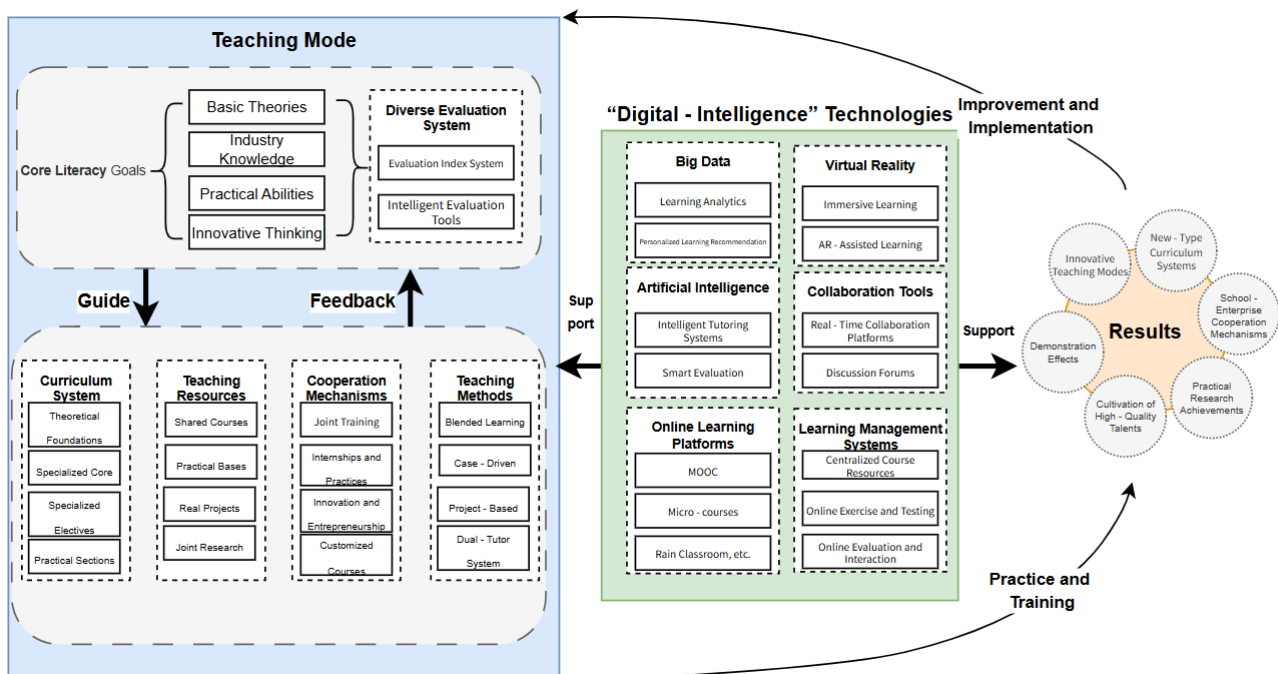


Figure 1. Overall framework of the graduate teaching model based on industry–education integration

3.1. Theoretical Framework

Literature Review: We survey and synthesize recent domestic and international scholarship on digital-intelligence technologies and on industry–education integration, conduct a systematic appraisal, and distill the strengths and weaknesses of existing teaching models.

Framework Construction: Building on the literature, we develop a theoretical framework for a big data graduate teaching model grounded in digital intelligence and industry–education integration, specifying the emphases, essentials, and procedural steps of the model.

3.2. Teaching Mode Design

Goal Setting: Based on current training schemes, we specify graduate learners' needs and practical-ability targets under a digital-intelligence and integration paradigm.

Curriculum Design: In partnership with enterprises, we co-analyze and design courses aligned with industry demand, including machine learning and deep learning, data visualization and business intelligence, and intelligent analytics and applications. A diversified pedagogy—blended learning, project-based learning, and case teaching—ensures tight coupling with hands-on practice.

Resource Integration: We integrate on- and off-campus resources—particularly those of partner enterprises such as Lanrui Software and Leju Robotics—to develop laboratories, internships, and project-based courses that meet teaching needs.

3.3. University–Enterprise Cooperation Mechanism

Mode Exploration: We pilot joint cultivation, internship-practice, innovation and entrepreneurship programs, industry-tailored courses, and collaborative research. [5]

Operationalization: (i) Establish a dual-supervisor system whereby university and enterprise mentors co-design courses and training projects. Students learn theory on campus while participating in real enterprise projects, achieving joint cultivation in and beyond the classroom. (ii) Build internship-practice models by setting up certified enterprise internship bases. Students regularly rotate into enterprises to hone skills and understand industry dynamics; alternatively, embed real enterprise projects into campus practice courses. (iii) Foster innovation and entrepreneurship through incubators and competitions; convert research outputs into cooperative research projects to raise the rate of technology transfer. (iv) Offer industry-customized courses after faculty–enterprise alignment; or embed industry-simulated projects within core courses and invite enterprise mentors to teach the latest industrial knowledge and technology trends. (v) Apply jointly for research projects and involve graduate students to sharpen their research capabilities and deepen their understanding of enterprise technical needs.

3.4. Practice Research

Case Studies: We have reached integration agreements with Lanrui Software and Leju Robotics to conduct practice in big data programs. We document experiences and challenges during implementation and extract critical success factors.

Project Implementation and Feedback: We field-test the designed teaching model, collect student and enterprise feedback on a regular cadence, and evaluate learning outcomes.

3.5. Teaching Evaluation and Continuous Optimization

We build a multi-dimensional, project-based evaluation system to track learning dynamically and to assess knowledge, skills, and competencies comprehensively. Based on feedback, we iteratively refine teaching methods to ensure quality while improving students' readiness for the labor market.

4. Core Issues in Industry–Education Integration for Graduate Training

4.1. Core Contradiction in University–Enterprise Collaboration and Solution Pathways

The core contradiction lies between universities' training cycles and enterprises' hiring needs. Universities follow fixed degree structures and curricula—typically two to three years for master's programs—and prioritize systematic, comprehensive knowledge transfer to cultivate future industry leaders. Enterprises, by contrast, require immediate, targeted productivity—especially in a fast-iterating digital-intelligence environment—and expect new hires to operate complex business systems and solve real problems from day one. This leads to a pronounced disconnect. For example, an enterprise embarking on an intelligent risk-control project may expect new graduates to handle challenging financial data and to refactor models right away, even though students may not yet have made the transition from theoretical study to practical application.

To address this, we recommend: (i) preserving core theoretical frameworks while adding 'industry-frontier' courses (e.g., lectures by executives and technical directors) and 'tools-in-practice' courses (e.g., Python data analysis, CAD drafting) to equip students with transferable skills; (ii) strengthening practice by importing 'enterprise scenarios' into campus, co-building 'industrial colleges' or 'training bases'; and (iii) incorporating internship reports, project deliverables, and skills certifications into graduation requirements, while inviting enterprise HR and technical leads to participate in thesis defenses to ensure outcomes meet real enterprise needs.

4.2. Core Issues in Implementing the Dual-Supervisor System

The dual-supervisor system is intended to realize joint cultivation, yet differences in roles, values, and working logics between academic and enterprise mentors can trigger tensions. In thesis work, for instance, the university mentor may require 'innovations grounded in theory', whereas the enterprise mentor may favor 'deploying mature solutions to solve pressing problems', placing students between academic innovation and practical delivery.

We propose convening a four-party meeting—university, enterprise, both mentors, and the student—before the dual-supervisor program begins (e.g., upon enrollment or before internships). The parties sign a Joint Training Agreement that specifies the core objectives of cultivation.

To mitigate timeline conflicts arising from misaligned 'academic' and 'project' cycles, mentors jointly map key milestones at the start of term (e.g., proposal and midterm checkpoints on campus; project go-live and client acceptance in enterprise), flag 'high-risk conflict periods', and reserve buffers in the student's plan (e.g., a one-week extension on coursework during urgent project phases; reduced enterprise workload two weeks before the thesis defense).

To reconcile evaluation criteria—'academic metrics' versus 'practical metrics'—we design a dual-dimension rubric covering both sets of priorities. The final grade (or thesis score) is jointly composed of a university mentor score (40–60%; emphasizing theoretical depth—conceptual accuracy, model applicability—and academic norms—

citation style, logical coherence) and an enterprise mentor score (40–60%; emphasizing practical effectiveness—project completion, tool proficiency—and role fit—teamwork, resilience). A joint defense mechanism ensures consensus: both mentors participate in midterm reviews and final defenses, with enterprise mentors commenting on industrial application value and university mentors ensuring academic rigor.

5. Conclusion

The central challenge for big data graduate education in the digital-intelligence era is dismantling the split between the ‘ivory tower of learning’ and the ‘arena of industrial practice’. Industry–education integration provides the most effective pathway to bridge the two. By constructing a university–enterprise–technology tri-collaborative framework, this paper explores training routes tailored to the field’s rapid iteration—from dynamically calibrated learning outcomes and modular curriculum restructuring to deeper dual-supervisor collaboration and a digitally empowered practice platform—and validates the model’s efficacy in enhancing graduates’ theory–technology–scenario competencies.

Beyond a replicable case for big data graduate education, this exploration reveals the underlying logic of integration in the digital-intelligence age: technological iteration is the engine; industrial demand, the compass; and education, a dynamic equilibrium that cultivates innovators who understand both algorithmic logic and industrial pain points. As AI and blockchain continue to intertwine with educational practice, we must further optimize human–machine collaboration—leveraging digital tools for resource matching and process tracking while preserving the university’s core role in nurturing humanistic literacy and critical thinking—so that integration truly becomes the converter that transports talent from laboratory to industry, continuously supplying the

digital economy with professionals who marry academic depth with practical sharpness.

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