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Original article

CONSTRUCTION AND APPLICATION OF A MULTI-SOURCE DATA-DRIVEN INTELLIGENT MODEL FOR INDUSTRY-RESEARCH DEMAND ANALYSIS IN SMART EDUCATION

CONSTRUCCIÓN Y APLICACIÓN DE UN MODELO INTELIGENTE IMPULSADO POR DATOS DE MÚLTIPLES FUENTES PARA EL ANÁLISIS DE LA DEMANDA INDUSTRIA-INVESTIGACIÓN EN EDUCACIÓN INTELIGENTE

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Abstract

In the context of the deepening development of smart education, resolving the structural misalignment between talent cultivation and industry demands has emerged as one of the core challenges in higher education reform. This study proposes a three-phase progressive framework, namely "Data Acquisition–Demand Modeling–Decision Output" to construct the multi-source data-driven intelligent analysis model for industry–research demand, integrating tripartite data from industrial, academic, and policy domains to drive the paradigm shift in educational decision-making from experience-based to data-driven approaches: 1) extracting industry demand profiles are extracted through topic modeling of unstructured recruitment texts to reveal composite competency frameworks; 2) identifying and tracking academic research hotspots and trends through bibliometric and keyword co-occurrence analysis; 3) dynamically calibrating model weights via policy document analysis based on strategic orientations. Applied to the artificial intelligence discipline as an empirical field, the model reveals three domain-specific characteristics: 1) industry demands demonstrate a trinity integration of technical proficiency, industrial applicability, and ethical awareness; 2) academic research undergoes an evolution from technological breakthroughs to scenario-based closed-loop construction, and further to socio-ethical value reconstruction; 3) policy priorities emphasize technological sovereignty and vertical scenario development. Then the model generates hierarchical competency matrices and dynamic-priority knowledge inventories to inform curriculum optimization, accompanied by four evidence-based talent cultivation strategies: 1) establishing a tripartite-integrated educational ecosystem; 2) strengthening industry–academia–research collaborative mechanisms; 3) creating adaptive knowledge renewal and ethical governance frameworks; 4) enhancing interdisciplinary scenario-based innovation capabilities. This study further expands the model's application scenarios, demonstrating its substantial potential for empowering smart education ecosystems, and outlines future research directions.

Key words: smart education, multi-source data fusion, industry–research demand analysis model, talent cultivation, educational decision support system, AI education

Resumen

En el contexto del creciente desarrollo de la educación inteligente, resolver el desajuste estructural entre la formación de talento y las demandas de la industria se ha convertido en uno de los principales desafíos de la reforma de la educación superior. Este estudio propone un marco progresivo de tres fases, denominado "Adquisición de Datos-Modelado de Demanda-Resultados de Decisiones", para construir el modelo de análisis inteligente basado en datos de múltiples fuentes para la demanda de la industria y la investigación. Este modelo integra datos tripartitos de los ámbitos industrial, académico y de políticas para impulsar el cambio de paradigma en la toma de decisiones educativas, pasando de enfoques basados en la experiencia a enfoques basados en datos: 1) la extracción de perfiles de demanda de la industria mediante el modelado temático de textos de reclutamiento no estructurados para revelar marcos de competencias compuestos; 2) la identificación y el seguimiento de los focos y tendencias de la investigación académica mediante análisis bibliométricos y de coocurrencia de palabras clave; 3) la calibración dinámica de las ponderaciones del modelo mediante el análisis de documentos de políticas con base en orientaciones estratégicas. Aplicado a la disciplina de la inteligencia artificial como campo empírico, el modelo revela tres características específicas del dominio: 1) las demandas de la industria demuestran una integración tripartita de competencia técnica, aplicabilidad industrial y conciencia ética; 2) la investigación académica evoluciona desde los avances tecnológicos hasta la construcción de ciclos cerrados basada en escenarios, y posteriormente a la reconstrucción de valores socio éticos; 3) las prioridades políticas enfatizan la soberanía tecnológica y el desarrollo de escenarios verticales. Posteriormente, el modelo genera matrices de competencias jerárquicas e inventarios de conocimiento con prioridad dinámica para fundamentar la optimización curricular, acompañados de cuatro estrategias de desarrollo de talento basadas en la evidencia: 1) establecer un ecosistema educativo tripartito e integrado; 2) fortalecer los mecanismos de colaboración entre la industria, la academia y la investigación; 3) crear marcos adaptativos de renovación del conocimiento y gobernanza ética; 4) mejorar las capacidades de innovación interdisciplinarias basadas en escenarios. Este estudio amplía aún más los escenarios de aplicación del modelo, demostrando su considerable potencial para potenciar los ecosistemas educativos inteligentes y describe futuras líneas de investigación.

Palabras clave: educación inteligente, fusión de datos multi-fuente, modelo de análisis de demanda de investigación e industria, cultivo de talento, sistema de apoyo a la toma de decisiones educativas, educación con IA.

Introduction

The underlying imperatives and paradigmatic advances for educational transformation in the era of digital intelligence are demonstrated in the article. The rapid iteration of artificial intelligence (AI) technologies and their deep integration with industrial transformation are reshaping the development paradigms of global higher education.[1] Against this backdrop, the core challenge for higher education institutions is to align talent cultivation with evolving industrial demands through systematic reforms.[2,3] To address the demand for core competencies required by new quality productive forces, it is imperative to establish a data-driven methodology for educational decision-making. This involves analyzing industry–research landscapes, adopting a demand-driven approach to optimize teaching content and methods, and ultimately cultivating top-notch innovative talents capable of adapting to technological iterations and industrial upgrades.[4]

<u>The Surging Tide of Intelligence and National Strategic Imperatives</u>: Interrogating Educational Modernization in Our Era. Driven by the convergence of AI technological innovation and national strategic demands, the education system is confronting unprecedented pressure to transform.[5,6] Currently, major countries worldwide are actively incorporating educational transformation within their AI strategic frameworks, seeking to gain a competitive edge in technology by innovating educational modes.[7]

The State Council’s Next Generation Artificial Intelligence Development Plan (*新一代人工智能发展规划*)[8] calls for building an intelligent and lifelong education system, positioning AI technology as the core driving force for educational modernization.[9] China’s Education Modernization 2035 and The Master Plan on Building China into a Leading Country in Education (*中国教育现代化2035及教育强国建设规划纲要*)[10] mandates the implementation of a national education digitalization strategy, leveraging AI to drive educational transformation.

Although China has explicitly set the goal of building an intelligent education ecosystem, it still faces multiple systemic challenges in the actual implementation process.[11,12] A particularly salient issue is the imbalance between the education system’s capacity for knowledge provisioning and the pace of industrial technological iteration. The course update cycles in the vast majority of higher education institutions lag far behind the tempo of technological evolution.[13,14] Consequently, the generational gap in teaching content is increasingly becoming a critical bottleneck constraining talent cultivation.

Intensifying Competition and Emerging Deficiencies: The Real-World Dilemma of the Domestic Education System. The intensification of the global competitive landscape has further magnified the deficiencies within the domestic education system. Developed countries, through policy guidance and resource integration, have established highly integrated education–innovation models involving industry, academia, and research. Their interdisciplinary curriculum systems are highly aligned with industrial demands, granting their graduates a significant competitive edge in employment within cutting-edge technological fields. In contrast, a persistent structural misalignment exists domestically between talent cultivation and industrial demands.[15-18]

The core competencies required for the vast majority of high-tech positions have not been effectively integrated into the curriculum systems of higher education institutions, and the misalignment between academic research orientations and engineering practice requirements further exacerbates the imbalance in talent supply and demand. Failure to rapidly respond to the demands of technological iteration and industrial upgrading will result in a disconnect in talent competitiveness, thereby constraining the realization of strategic goals such as “China Intelligent Manufacturing” and “Educational Modernization”.

Mechanism Obstructions and Accumulated Contradictions: The Endogenous Chronic Issues in Education System Operation. Deeper contradictions stem from the practical predicaments inherent in the operational mechanisms within the education system itself. Traditional decision-making models rely excessively on experiential judgment and the vast majority of teaching units lack the capacity to dynamically track technological frontiers, resulting in the updating of teaching content frequently lagging behind the pace of industrial transformation.[19-21]

Simultaneously, industry–education collaboration mechanisms have not yet progressed beyond formalistic cooperation. The vast majority of university–enterprise partnership projects have failed to establish resource integration channels that span the entire talent cultivation lifecycle. More alarmingly, the education system exhibits a widespread weakness in its early-warning capabilities against technological obsolescence risks and its corresponding countermeasures. Furthermore, the dynamic alignment between program/discipline offerings and market demands remains largely theoretical.[22] Collectively, these mechanistic deficiencies lead to a “time-lag” dilemma in talent cultivation—by the time the education system completes a cycle of teaching reform, industrial technological standards have often progressed to a new stage.

Entrenched Paradigms and Model Constraints: Methodological Limitations in Traditional Decision Analysis. Traditional educational decision-making models predominantly rely on either one-dimensional policy-driven analysis or lagging graduate feedback data, rendering them inadequate for capturing the micro-fluctuations in technological iteration and market demand in real-time; while industry demand analysis models often focus on static job skill profiles or isolated corporate recruitment data, lacking effective integration of academic frontier dynamics and macro-level policy traction.[23] More critically, these two types of models typically operate in silos, failing to establish a dynamic and synergistic analytical framework that integrates the three dimensions of educational supply, technological development, and industrial demand.[24,25] This fragmentation results in delayed demand identification, limited predictive accuracy, and an inability to support the forward-looking adjustment of teaching content. The key to breaking this impasse lies in propelling the education system towards a paradigm shift from experience-driven to data-driven decision-making.[26,27]

This necessitates establishing a dynamic response mechanism that traverses technological development, industrial demand, and educational supply, leveraging intelligent means to enable the continuous evolution of the knowledge system. Only by constructing a forward-looking and resilient education ecosystem can we resolve structural contradictions, break free from the passive stance of "catch-up development", cultivate new-quality talents equipped with both innovative capacity and practical capabilities, and thereby provide sustained underpinning for national strategies.[28,29]

To address these bottlenecks, this study proposes to construct an intelligent multi-source data-driven model for analyzing industry–research demand. This model aims to overcome the limitations inherent in traditional qualitative analysis in pedagogy, and to introduce a tripartite computational education research paradigm integrating recruitment data mining, academic trend forecasting, and policy text analysis. Furthermore, it seeks to explore a multi-source data fusion methodology for educational decision-making, thereby providing methodological innovation for the scientification of educational decision-making. Concurrently, leveraging the "I-A demand+curriculum supply" dynamic response mechanism, this study will establish a multi-dimensional and quantifiable approach to curriculum optimization.

This approach will facilitate the development of a data-driven Educational Decision Support System to achieve real-time mapping between curriculum content and I-R demand, consequently generating replicable curriculum optimization pathways. This integrated solution aims to address the deep-seated issues of "lagging knowledge updates" and the "disconnect between industry, education, and research", providing higher education institutions with a scientific decision support framework, and thereby contributing to the construction of an intelligent education ecosystem.

Methodology about Paradigm Construction: A Multi-Source Data-Driven Intelligent Model for Industry–Research Demand Analysis

This study proposes a three-stage progressive framework for the Industry–Research demand intelligent analysis model, as illustrated in **Figure 1**, encompassing Data Acquisition, Demand Modeling, and Decision Output. The core of this model comprises three key modules:

1. Talent Demand Profiling based on Unstructured Recruitment Texts,
2. Research Status Analysis and Trend Hotspot Forecasting based on Journal Databases,
3. Macro-Level Policy Guidance Analysis and Model Result Fine-Tuning based on Policy Texts.

Together, these modules comprehensively integrate data sources from the industrial, academic, and policy spheres. The key technical methods are outlined below (**Figure 1**):

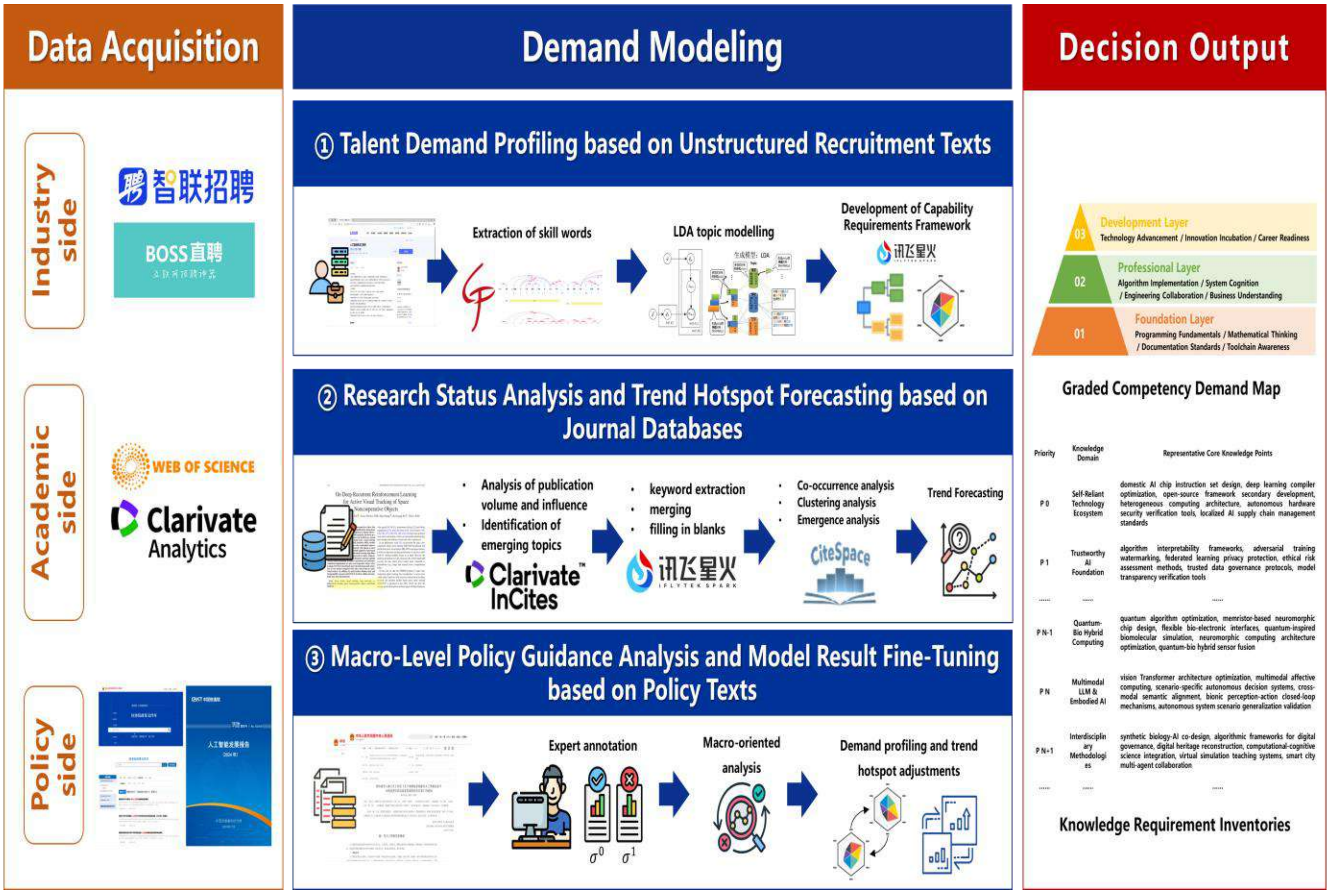


Figure 1. Framework for Multi-Source Data-Driven Intelligent Model for Industry–Research Demand Analysis
Source: own elaboration

Module 1: Demand Extraction–Intelligent Generation of Competency Maps.

This module employs a Python-based targeted crawler system to collect raw data from recruitment websites. The collected data is then processed through multiple cleansing rules to construct a purified text corpus. Utilizing a competency-oriented stop word lexicon to filter out semantic noise, the module leverages the Latent Dirichlet Allocation (LDA) model[30] to uncover latent competency topics. This enables the precise deconstruction of the industry's competency requirements for specialized talents.

Module 2: Frontier Insight–Metric Tracking of Academic Ecosystem Evolution.

An authoritative dataset is constructed by filtering for ESI Highly Cited Papers/Hot Papers within the Web of Science Core Collection. The InCites™ platform is utilized to analyze disciplinary development trends and emerging technological themes. Simultaneously, CiteSpace 6.2. R4 is employed to deeply analyze keywords extracted by the Spark LLM developed by iFLYTEK. This facilitates co-occurrence network analysis, cluster evolution tracking, and innovation burst detection, thereby uncovering the evolution of domain knowledge structures and paradigm shifts.[31]

<u>Module 3: Policy Decoding–Hierarchical Refinement of Strategic Directives</u>.

A multi-level text corpus is constructed based on policy authority hierarchy and industry impact. Expert evaluation is used to extract high-frequency strategic terms and identify key development orientations. This process generates both the constraints and opportunity spaces for curriculum system optimization.

In summary, this model takes three-dimensional inputs: industrial competency demands, academic frontier trends, and policy strategic directives. At the industrial end, it extracts competency inventories via demand profiling; at the academic end, it predicts technological requirements through bibliometric analysis; and at the policy end, it anchors developmental coordinates by text analysis. These three-source data streams are fused with dynamic weighting to generate both hierarchical competency demand maps and knowledge requirement inventories. Regular updates of the data sources enable the continuous iteration of demand response. This provides a scientific foundation for the dynamic adaptation of higher education curriculum supply.

Empirical Insights: Deep Decoding of New-Quality Talent Demand in Artificial intelligence under Model Guidance

The field of AI, characterized by its exponential evolution rate and the structural alignment pressures between industry and education, serves as a critical exemplar for observing the evolution of new-quality talent demand. Therefore, this part utilizes the AI discipline as an empirical testing ground, leveraging the aforementioned “Multi-Source Data-Driven Intelligent Model for Industry–Research Demand Analysis” through a four-dimensional analytical framework encompassing: structured parsing of industrial demand, panoramic mapping of the academic ecosystem, dynamic assessment of frontier trends, and in-depth deciphering of policy directives. This framework enables the robust interpretation of the competency spectrum and knowledge structure requirements for new-quality talents within this domain. Consequently, it furnishes a precise targeting basis for the restructuring of higher education curriculum systems.

(i) <u>Structured Parsing of Industrial Demand: Integration of Technical–Industrial–Ethical Competencies</u>

This study conducted in-depth mining of the industrial competency corpus based on LDA topic modeling. The optimal topic structure was determined through topic coherence evaluation and interactive visual validation. Subsequently, guided by dual-dimensional quantitative metrics—namely, feature term frequency distribution and semantic uniqueness—we condensed the key competency themes and their dominant feature term clusters, as presented in **Table 1**.

Theme Rank	Keyword Weight	Dominant Feature Terms	Theme Naming	Theme Description
1	19.7%	research, standards, industry, international, policy, evaluation, algorithm, formulation	Policy Research & Industry Standardization	Focuses on top-level industry design, policy tracking & interpretation, and international standards alignment, reflecting macro-planning capabilities.
2	14.5%	Python, algorithm, machine learning, TensorFlow, distributed, deployment, training	Algorithm Development & Model Optimization	Concentrates on deep learning framework application, algorithm engineering implementation, and distributed training, indicating core technical competencies.
3	11.4%	system architecture, digital twin, communication protocol, intelligentization, hardware integration	Systems Engineering & Digital Transformation	Involves complex system design, digital twin technology implementation, and cross-platform integration capabilities.
4	10.7%	mathematical foundation, logical thinking, automation, testing & verification, documentation standards	Foundational Technical Competencies	Reflects fundamental qualities including mathematical proficiency, engineering standardization awareness, and technical documentation skills.
5	10.2%	team collaboration, project management, cross-departmental communication, accountability, certification systems	Team Leadership & Project Execution	Emphasizes team leadership, cross-departmental coordination, and full-cycle project management experience.
6	10.1%	multimodal, solution, product iteration, market research, implementation	Productized Solution Design	Prioritizes requirement translation, end-to-end product development, and commercialization capabilities.
7	8.1%	edge computing, model compression, hardware adaptation, real-time inference, accuracy optimization	Embedded AI & Performance Optimization	Addresses edge deployment, model lightweighting, and hardware-level performance tuning.
8	7.7%	patents & publications, large language models, knowledge transfer, academic conferences, outcome commercialization	Research Innovation & Commercialization	Embodies academic research capability, patent output, and industry–academia–research translation experience.
9	7.6%	data visualization, technical documentation, presentation, stress tolerance, business understanding	Technical Communication & Business Support	Highlights technical communication skills, customer requirement interpretation, and solution presentation proficiency.

Table 1. Key Competency Themes and Dominant Feature Term Clusters
Source: own elaboration

Policy Research & Industry Standardization emerge as core themes, highlighting the industry's heightened reliance on top-level design capabilities during its ecosystem development phase. Enterprises are urgently requiring multidisciplinary talents capable of coordinating the dynamic alignment between technology research & development and industrial policies, who must possess both technological literacy and policy sensitivity, to navigate the restructuring of global technology governance frameworks.

The technology implementation themes focus on the synergy between algorithm development and embedded deployment, reflecting industry demand for end-to-end capabilities spanning from laboratory to production line, as well as the value shift in AI from theoretical innovation to engineering implementation and the persistent demand for core technical competency talents. Meanwhile, Systems Engineering & Digital Transformation converge with Productized Solution Design to form a competency loop: This bidirectional demand for technological construction and commercial deconstruction capabilities fundamentally constitutes a dual assessment of systematic thinking and business acumen in talents.

Through further analysis and synthesis of the dominant feature words and descriptions across these themes, a tiered competency labeling system is established as presented in **Table 2**, transforming discrete themes into a quantifiable competency assessment framework.

Tier-1 Competency	Tier-2 Competency	Related Themes
Technical Implementation	Algorithm Engineering	2, 7
	System Architecture Design	3
	Hardware Co-Development	7
Industry Solutioning	Requirements Engineering	6
	Technology Commercialization	6, 9
	Standardization Development	1
Research & Innovation	Academic Research	8
	Technology Foresight	1
	Research–to–Practice Translation	8
Engineering Management	Agile Development	5
	Quality Assurance	4, 7
	Resource Allocation	5
Professional Literacy	Engineering Ethics	4
	Technical Knowledge Transfer	9
	Stress Resilience	9

Table 2. Tiered Competency Labeling System
Source: own elaboration

With Technological Implementation competency serving as the foundational layer, the coupling between its secondary labels reveals the industry’s emphasis on research–application integration capabilities. Enterprises require talents to master fundamental development tools, possess practical technology implementation skills, and architect solutions from a system-level perspective, thereby bridging the chasm between laboratory prototypes and production environment deployment, essentially constituting a standardized definition of code–chip–system collaborative development competency. Industry Solutioning competency, through the linkage of requirements engineering and technology commercialization, builds a complete chain of demand insight-solution design-value verification. This closed-loop competency necessitates practitioners' dual command of technological rationality and market acuity.

The demand for Research & Innovation competency is more breakthrough-oriented, incorporating academic research and technology transfer into a unified evaluation dimension, emphasizing the infusion of theoretical achievements into industrial practice through knowledge transfer mechanisms. This balance between academic excellence and industrial applicability directly addresses the pain point of disconnection between theoretical research and commercial practice in current education systems, highlighting the urgency of deep industry–academia–research integration. The Professional Literacy dimension, through the juxtaposition of engineering ethics and technical communication, redefines the social role of technical talents—transitioning from mere technical executors to technology-society interface builders, while addressing their moral standards and professional persona development, manifesting distinct traits of the contemporary era.

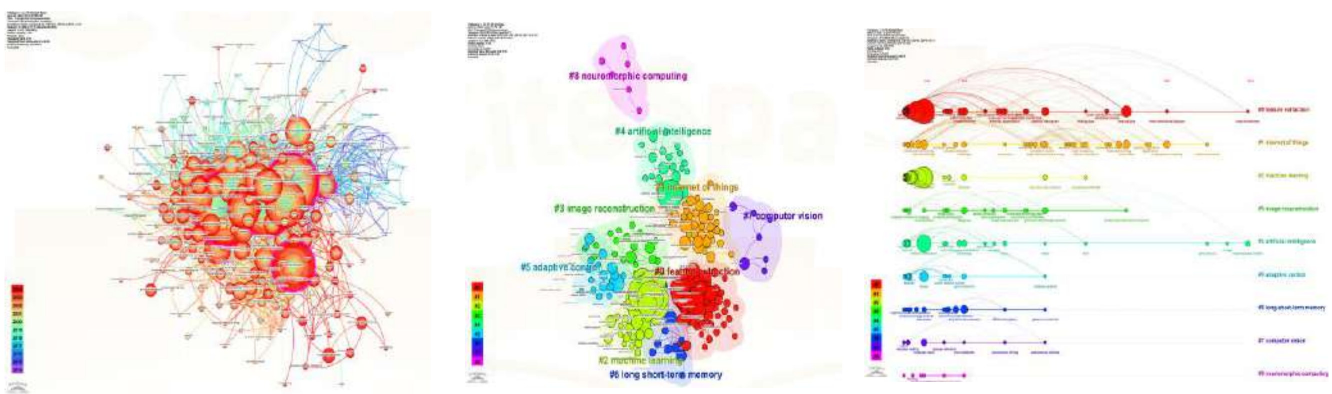
The foregoing analysis reveals that AI talent demand has transcended the traditional unidimensional technocracy, shifting toward a "technology–industry–ethics" triadic integration competency model. This shift is marked by a dual emphasis on technological depth and industrial breadth, a synergy between academic innovation and commercial application, and an integration of professional competencies with ethical and occupational literacy.

(ii) Panoramic Mapping of Academic Ecosystem: Evolution of Innovation Poles through Steady State Shifts and Fragmented Reconfiguration

Over the past decade, AI research has exhibited an asymmetric symbiosis between scale expansion and impact evolution: Research scale demonstrates exponential growth, particularly during the 2014–2020 high-growth phase catalyzed by data-driven paradigms and the "technological breakthrough–policy incentive–capital infusion" positive feedback loop, triggering clustered emergence of highly cited papers; whereas academic impact reveals a rise-then-decline trajectory, with a marginal citation decrease after 2021 driven by technology bubble dissipation and research focus deepening, further exacerbated by academic output spillover and citation time-lag effects from corporate closed systems, collectively intensifying metric value leakage. This disequilibrium intrinsically mirrors a dual transformation in technology life cycles and research paradigms—shifting from efficiency-priority to complex system governance, refracting the dynamic game between open innovation and value rationality in global scientific ecosystems, propelling academic output toward sustainable innovation paradigms.

The keyword co-occurrence network further unveils a dialectical unity structure within the domain's knowledge system: with the core zone exhibiting high aggregation—central hubs such as deep learning and neural networks—sustaining technological continuity between early hotspots and traditional methodologies, while the periphery dynamically expands, extending into scenario depth via branches such as CNN and reinforcement learning, manifesting a symbiotic logic between technological core stability and application diversification. The temporal dimension clearly demonstrates a three-phase paradigm shift: From 2014 to 2016, the focus was on fundamental research and development in model architecture and general algorithm optimization. Between 2017 and 2021, advancements shifted toward fine-grained innovations like attention mechanisms and GANs. Since 2022, the field has entered the LLM-driven pretraining paradigm and multimodal fusion phase, forming a “technology–data–computing power” triangle-driven ecosystem.

Furthermore, nodes like Blockchain and Federated Learning construct knowledge bridges between privacy computing and distributed systems, while Physics-Informed Neural Networks and Digital Twins propel cross-disciplinary integration in engineering modeling. These emerging themes—despite being constrained by domain-specific knowledge barriers, data heterogeneity, and the absence of evaluation standards—signal an inevitable transition from isolated technological advances to a systemic ecology integrating technology, application scenarios, and disciplines. To support this transformation, higher education must urgently reform its supply-side by dismantling disciplinary silos and building mechanisms for cross-disciplinary knowledge integration to overcome developmental bottlenecks.



(a) Keywords Co-occurrence Network (b) Clustered Network View (c) Clustered Timeline View

Figure 2. Keywords Co-occurrence Network and Clustered Visualization Results

Source: own elaboration

Clustering analysis of scientific knowledge maps reveals nine core knowledge clusters that underpin contemporary AI research. These form a technology layer spanning the complete innovation chain of algorithm–architecture–hardware, an application layer enabling deep convergence in scenarios like healthcare and industry, and a discipline layer generating a dynamic and complex knowledge topology through cross-evolution. Together, these layers constitute a multidimensional ecosystem of in-depth knowledge development, characterized by three structural features.

The stability and innovation of the technological foundation manifest a dual-track parallel evolution pattern between traditional methods and emerging architectures. Core technology clusters (**Table 3**), represented by feature extraction and machine learning, demonstrate a symbiotic interplay between traditional algorithms and deep learning frameworks. Traditional models maintain their irreplaceability in resource-constrained scenarios due to their advantages in interpretability and low computational requirements; deep learning, through architectural innovations and leaps in parameter scale, has gradually become the dominant paradigm in pattern recognition. These two approaches constitute a functional complementarity—traditional methods provide a stability anchor for technological evolution, while deep learning drives paradigm breakthroughs in data-intensive domains through its end-to-end learning capability, collectively sustaining the dynamic equilibrium of the technological ecosystem.

Cluster ID	Cluster Name	Size	Silhouette	Core Characteristics	Research Orientation	Technical Connections & Application Domains
0	Feature Extraction	50	0.859	Largest cluster with high internal consistency; foundational AI support	Methodological Core	Computer vision, NLP, and other domains requiring fundamental feature extraction
1	Internet of Things	41	0.896	Embodies deep AI-IoT integration trends	Cross-domain Synergy	Edge computing, smart sensing, autonomous decision-making in IoT scenarios
2	Machine Learning	32	0.957	Highly cohesive technical core focused on model optimization & interpretability	Methodology Evolution	Universal framework for AI tasks emphasizing generalization capability and theoretical breakthroughs
3	Image Reconstruction	21	0.906	Cutting-edge interdisciplinary high-precision applications	Technology Penetration	Medical imaging, remote sensing, and other high-fidelity reconstruction/enhancement scenarios
4	Artificial Intelligence	20	0.991	Conceptual & ethical focus with extreme internal cohesion	Theoretical Paradigm	Foundational AI concepts, ethical frameworks, and societal impact studies
5	Adaptive Control	18	0.961	Engineering integration of control science and AI	Application-Driven	Industrial control systems: complex system modeling, real-time optimization
6	Long Short-Term Memory	13	0.925	High-frequency DL technique (LSTM)	Instrumental Methodology	Sequential modeling tasks: NLP, time-series prediction
7	Computer Vision	7	0.918	Sustained vitality integrating classical and emerging methods	Scenario-Driven Innovation	Core technical ecosystem for image understanding, object detection
8	Neuro morphic Computing	6	0.983	Brain-inspired computing models enabling new paradigms	Frontier Breakthrough	Next-gen AI computing: bio-inspired architectures, low-power hardware research & development

Table 3. Core Cluster Details
Source: own elaboration

The dynamic migration of research hotspots manifests a technology lifecycle shifting from algorithm optimization to scenario-driven approaches. From 2014 to 2016, research efforts focused on tackling fundamental theoretical challenges. Between 2017 and 2020, with enhanced computational power and data accumulation, a technological closed-loop system for privacy protection and localized decision-making was established.

From 2020 to 2022, the field entered a phase of deep feedback, where Large Language Models disrupted traditional research frameworks, real-time industrial demands inversely drove the deepening of control theory, catalyzing innovations in complex system modeling and multi-agent collaboration. From 2022 to the present, Industrial IoT and embodied intelligence have propelled the construction of a symbiotic ecosystem characterized by “demand defines technological boundaries, while technology empowers scenario evolution”, achieving a historic leap from a linear technology-driven paradigm to a cross-layer collaborative paradigm.

The efficient mechanism of interdisciplinary integration sees knowledge networks fostering innovation fission through the interpenetration of methodologies, while reconstructing disciplinary boundaries via a problem-oriented mechanism. Representative domain integrations (e.g. neuromorphic computing, image reconstruction) drive the development of novel architectures and paradigm shifts in image processing, while adaptive control and computer vision address multi-scenario demands through methodological integration. Such high-density, small-scale clustering signifies a structural transformation in the research paradigm: a shift from isolated technological breakthroughs to a holistic chain coupling encompassing “original innovation in fundamental theory—collaborative validation in engineering technology—rigid ethical governance constraints”, continually reconstructing the underlying cognitive logic of the technological ecosystem through cross-hierarchical knowledge flow.

(iii) <u>Dynamic Trend Analysis of AI Frontiers: A Paradigm Shift from Tool Innovation to Ecosystem Restructuring</u>

Based on the analysis of burst keywords, this study identifies two major patterns characterizing academic hotspots across different periods in this field: “long-tail infiltration of foundational technologies” and “pulse-like bursts driven by application scenarios”. Early high-intensity burst keywords demonstrate lasting influence, indicating that fundamental algorithmic research can continuously permeate emerging fields through functional differentiation. After 2019, the focus of burst keywords has shifted towards application-oriented technologies characterized by short-cycle bursts, concentrating on vertical domains such as smart manufacturing, highlighting the immediate traction of industrial demands on academic research. By 2022, highly interdisciplinary burst keywords, such as Graph Neural Networks and attention mechanisms, have formed technological resonance with research on Large Language Models and Generative AI, propelling the pre-training paradigm to restructure disciplinary knowledge systems while simultaneously catalyzing an eruption of ethical issues. This evolutionary trajectory—progressing from foundational support, through scenario-driven phases, to paradigm disruption—reflects the discipline-wide development process of AI, characterized by a paradigm shift from tool innovation to ecosystem restructuring.

Furthermore, by analyzing over a hundred AI-related emerging topics, this study reveals three salient characteristics of the research frontier in this field. (1) Deep Integration of Technology and Scenarios: Specialized Innovation in Vertical Domains. Emerging topics demonstrate high scenario-specificity and technological adaptability in domains such as healthcare, education, and manufacturing. These topics exhibit a clear trend of integrated technology stacks within vertical domains, reflecting academia’s shift from supplying generic technologies towards responding to complex scenario demands. This shift is driving the evolution of technology from a tool-oriented function towards becoming ecosystem-level infrastructure. (2) Dynamic Reconstruction of Disciplinary Boundaries:

The Emergence of Cross-Disciplinary Knowledge Networks. Emerging topics exhibit strong interdisciplinary attributes, with knowledge integration manifesting three distinct modes including instrumental convergence, methodological convergence, and problem-driven convergence, and traditional disciplinary barriers are dissolving under the dual pressures of technological evolution and problem-oriented research. Such interdisciplinary research often exhibits exceptionally high innovation density. (3) Enhanced Rigidity of Ethical Governance: From Add-on Constraints to Endogenous Architecture. Ethical governance is implicated in 40% of emerging topics, exhibiting a trend of governance technologicalization. On the one hand, endogenous technical governance has become mainstream; on the other hand, the scope of governance has expanded to encompass the technological ecosystem level; additionally, ethical engagement is shifting from passive response to active anticipation.

Based on the preceding analysis, we foresee the following trends emerging in future AI research:

1. Cross-Modal Fusion Breakthroughs in Trustworthy-Enhanced Intelligent Architectures. Future algorithmic innovations will focus on the deep integration of lightweight dynamic architectures with physical laws, aiming to overcome the Pareto trade-off between energy consumption and generalization capability, thereby driving the transition of models from black-box to white-box architectures. The unique advantages of quantum neural networks in hyperparameter optimization and high-dimensional feature mapping may reshape the theoretical foundations of intelligent computing. Meanwhile, hybrid modeling techniques coupling data-driven approaches with physical equations hold promise for overcoming the interpretability bottlenecks of traditional AI in complex system modeling, offering more robust solutions for critical domains.
2. Full-Chain Upgrade of Intelligent Manufacturing Empowered by Digital Twins and Causal Reasoning. The focus of industrial scenario reconstruction is shifting from single-modality recognition to full-chain optimization encompassing multimodal perception, uncertainty quantification, and causal reasoning, catalyzing three paradigm shifts: enhanced precision in digital-physical mapping, real-time decision control, and secure collaborative learning. Digital twin-based full-element modeling enables root cause analysis of manufacturing defects, while the integration of federated learning and edge computing supports the formation of cross-factory knowledge-sharing networks. Furthermore, the convergence of Industrial IoT and generative AI fosters the development of adaptive production systems, driving a comprehensive upgrade across the manufacturing sector.
3. Paradigm Reconstruction of Cross-Scale Intelligence Driven by Quantum–Biological Fusion. Deep convergence of neuromorphic computing and quantum machine learning will open new research frontiers. Quantum-inspired computing-in-memory brain-like chips may break through the constraints of traditional architectures, enabling biological-level energy-efficient computing. The application of quantum annealing algorithms in biomolecular simulation has the potential to revolutionize drug discovery pipelines. The integration of multiomics data with quantum machine learning methods could lay the foundation for precision medicine models with unprecedented granularity. The fusion of flexible bio-interfaces and quantum sensing technologies may pave the way for a new generation of neuromodulation devices.

4. Reinforcement of AI Governance Technologies Driven by Dynamic Compliance. The explosive growth of generative AI is driving upgrades to the tripartite governance architecture encompassing technology, ethics, and law. Blockchain-based verifiable computation frameworks may establish new standards for cross-border data. The integration of adversarial training with digital watermarking could develop end-to-end traceability systems for AIGC. Green computing paradigms through hardware-algorithm co-optimization will reshape energy efficiency evaluation standards for AI systems. The innovative integration of privacy-preserving computation offers potential solutions to the zero-sum dilemma between data value extraction and privacy protection in medical data sharing scenarios.
5. Physical–Digital Convergence Revolution Driven by the Fusion of Embodied Intelligence and Scientific Computing. By leveraging closed loops of multimodal perception and reinforcement learning, embodied intelligence systems will transcend structured scenario constraints and develop autonomous decision-making capabilities in extreme environments. Quantum-classical hybrid computing architectures may catalyze a "computing–as–experimentation" paradigm for scientific research. Breakthroughs in neural interface technologies could unlock new dimensions in consciousness digital twin research, and despite ethical challenges, are already demonstrating transformative potential in interventions for neurodegenerative diseases.

(iv) <u>In-Depth Deciphering of Policy Directives: Strategic Anchoring of Autonomous Breakthroughs and Mandatory Governance.</u>

This empirical study constructs a multi-tiered textual framework comprehensively covering the policy transmission chain spanning strategic planning, industry standards, and regional implementation, with high-frequency strategic keywords extracted through expert evaluation, selected examples of which are presented in **Table 4**. Analyzed texts include: National-level guiding documents such as Next Generation Artificial Intelligence Development Plan (新一代人工智能发展规划).[8]

Table 4. High-Frequency Strategic Keywords

Keyword	**Representative Policy Documents & Provisions**
Self-reliance & Controllability	Core Technology Breakthrough Chapter of *"New Generation Artificial Intelligence Development Plan"*
Industrial Convergence	Industrial Digitalization Deployment Section of *"14th Five-Year Plan for Digital Economy Development"*
Trustworthy AI	Algorithm Explicability Mandates request of *"Standardization Guidelines for AI Ethics Governance"*
Computing Infrastructure	Computing Power Network Construction Initiatives in Beijing/Shanghai Municipal Policies
Application Scenario-Driven	Priority Scenario Lists (Healthcare/Manufacturing) of *"China AI Development Report"*
Data Sovereignty	Cross-border Data Flow Governance Provisions of *"Data Security Law"*

Source: own elaboration

Data Security Law (数据安全法,[31,32] and 14th Five-Year Plan for Digital Economy Development ("十四五"数字经济发展规划)[33]; Industry-specific implementation guidelines including China AI Development Report (中国人工智能发展报告)[34] and Standardization Guidelines for AI Ethics Governance (人工智能伦理治理标准化指南)[35]; Regional pilot initiatives such as Beijing Measures for Promoting Generative AI Innovation (北京市促进通用人工智能创新发展若干措施)[36] and "Computing Huangpu" Intelligent Computing Action Plan ("算力浦江"智算行动实施方案).[37]

Analysis of keyword-policy objective linkages reveals three critical development orientations.

1. Tech Autonomy Breakthrough Orientation: Next Generation Artificial Intelligence Development Plan emphasizes open-source ecosystems and self-controlled software/hardware systems, prioritizing policy interventions in bottleneck technologies such as GPU architectures and deep learning compilers. This orientation necessitates incorporating instruction set optimization for domestic AI chips and secondary development of open-source frameworks into hardware curricula to strengthen autonomous tech ecosystem capabilities.
2. Mandatory Ethics Governance Orientation: Standardization Guidelines for AI Ethics Governance establish full-cycle governance through institutional mechanisms including algorithm registration and deepfake traceability. Policy mandates compel the addition of teaching modules like AI security penetration testing and compliance-by-design, cultivating internalized governance competencies among technologists.
3. Scenario Deepening Orientation: China AI Development Report designates demonstration projects (e.g. smart manufacturing, AI healthcare), using scenario catalog management to drive technology diffusion. This drives development of contextualized teaching cases (e.g. industrial visual inspection, medical image analysis) to enhance closed-loop mapping of technology–scenario–demand linkages.

By dynamically capturing mandatory clauses and incentive mechanisms in these policies, we propose three priorities: domestic substitution of core technologies, penetration rate increase in key industries, and security–trustworthiness capacity building. Curriculum optimization based on this framework ensures policy compliance while capturing strategic dividends, achieving dynamic calibration between industry–research demands and educational provision.

Value Expansion: Multidimensional Pathways for Model-Empowered Smart Education Ecosystem Development

(i) Model Reshaping: Iterative Strategy for Higher Education Talent Cultivation Based on Demand Insights

1. Mapping Model Analytics to Educational Decision Support in Empirical Fields

Leveraging industry–research demand analytics from AI empirical fields, the previously described multi-source data-driven intelligent analysis model generates the hierarchical competency demand map (**Figure 3**) and prioritized knowledge demand inventories (**Table 5**), offering targeted support for educational decision-making. The hierarchical competency map categorizes competencies into foundational, specialized, and developmental tiers based on technology maturity levels and career development orientation, while the knowledge inventory incorporates dynamically prioritized knowledge units.

Figure 3. Hierarchical Competency Demand Map
Source: own elaboration

Table 5. Parts of Prioritized Knowledge Demand Inventories

Priority	Knowledge Domain	Representative Core Knowledge Points
P 0	Self-Reliant Technology Ecosystem	domestic AI chip instruction set design, deep learning compiler optimization, open-source framework secondary development, heterogeneous computing architecture, autonomous hardware security verification tools, localized AI supply chain management standards
P 1	Trustworthy AI Foundation	algorithm interpretability frameworks, adversarial training watermarking, federated learning privacy protection, ethical risk assessment methods, trusted data governance protocols, model transparency verification tools
……	……	……
P N-1	Quantum-Bio Hybrid Computing	quantum algorithm optimization, memristor-based neuromorphic chip design, flexible bio-electronic interfaces, quantum-inspired biomolecular simulation, neuromorphic computing architecture optimization, quantum-bio hybrid sensor fusion
P N	Multimodal LLM & Embodied AI	vision Transformer architecture optimization, multimodal affective computing, scenario-specific autonomous decision systems, cross-modal semantic alignment, bionic perception–action closed-loop mechanisms, autonomous system scenario generalization validation
P N+1	Interdisciplinary Methodologies	synthetic biology-AI co-design, algorithmic frameworks for digital governance, digital heritage reconstruction, computational-cognitive science integration, virtual simulation teaching systems, smart city multi-agent collaboration
……	……	……

Source: own elaboration

Holistically, the Intelligent Model for Industry–Research Demand Analysis constructed in this study, through multi-source data fusion, reveals co-evolutionary patterns of technical–industrial–academic competency demands in the AI domain. The industrial sector has transcended the traditional unidimensional technical framework, developing a composite competency architecture encompassing technical depth, industrial integration, and ethical literacy, manifesting novel characteristics including synchronized deepening of algorithmic innovation and industrial scenario penetration, dual-drive mechanism between research breakthroughs and commercial translation, and nested symbiosis of professional competencies with occupational ethics, signaling a paradigm shift from tool-based development to ecosystem-oriented innovation in industrial demands.

The academic sector demonstrates a triple-helix breakthrough dynamic: at the technical layer, shifting from algorithm optimization to systemic innovation across architecture–hardware–theory; at the application layer, transitioning from empowering discrete scenarios toward fused physical–virtual–social spaces; at the governance layer, establishing a full-cycle dynamic governance system with prevention–control–evolution mechanisms.

These breakthroughs are catalyzing the qualitative transformation of AI into intelligent infrastructure—technologically through physics-embedded and bio-inspired computing transcending conventional paradigms, applicative via open-environment cognition enabling scenario expansion across dimensions, and in governance through resilient ethical frameworks balancing innovation and risk. Policy interventions provide institutional scaffolding for this evolution through technological autonomy breakthroughs, mandatory ethics governance, and scenario deepening pathways.

The tripartite synergy reveals the core developmental logic of AI: technological innovation must deeply couple with industrial penetration and academic breakthroughs require value reconstruction under ethical constraints. These elements converge into a closed-loop ecosystem, in which technological advances propel industrial upgrading, policy frameworks delimit development boundaries, and market demands feed back into innovation.

In-depth analysis reveals that the restructuring of talent demand in the AI industry is driven by three forces: Under the technology–industry co-configuration mechanism, technological breakthroughs like algorithmic engineering and digital twins catalyze full-chain competency demands spanning from Research & Development to deployment. The accelerating industrial ecosystem development drives policy coordination and commercialization, demanding interdisciplinary talents equipped with both technological understanding and sensitivity to industrial policies. The pervasive integration of technology into society elevates ethical governance and communication skills to core competencies, propelling talent towards roles at the intersection of technology and society, ultimately shaping a dynamic adaptation framework characterized by technical depth, systematic integration, and value transformation.

Meanwhile, the evolution of academic research trends is steered by four-dimensional dynamics: Within the endogenous technological cycle, the positive feedback loop among data-computing power-algorithms drives technological iteration. Scenario differentiation, pulled by industrial demand, compels the divergence of research themes and drives technology to upgrade from an efficiency tool to a value engine.

Under societal regulatory pressure, global privacy regulations institutionalize ethical constraints as technological variables. Cross-disciplinary convergence, in turn, infuses new momentum into AI and expands the frontiers of innovation. Furthermore, the standardization within open-source communities and the culture of contests accelerates technology diffusion, fostering a synergistic configuration of hardware-driven development, open-source empowerment, and demand diversification.

2. Optimization of Talent Cultivation Strategies Driven by the Model

Against this backdrop, this study proposes the following four recommendations for optimizing talent cultivation strategies in the AI discipline.

<u>Constructing a Three-Dimensional Integrated Education System</u>.

AI education must transcend traditional disciplinary boundaries to establish a three-dimensional integrated cultivation framework encompassing core technologies, industrial ecosystems, and social ethics. At the core competency level, it should strengthen integrated teaching of algorithm architecture, hardware co-design, and system design, leveraging authentic scenario projects such as digital twins and edge computing to cultivate students' engineering mindset for tackling full-chain challenges from the lab to the production line.

At the industrial cognition level, it should embed curricular modules such as policy analysis and standard formulation, utilize industry–academia–research (IAR) platforms to conduct practical training on technology commercialization, thereby facilitating the transformation of academic achievements into value-adding activities like patent pool operation and solution design. Meanwhile, at the ethical governance level, it needs to integrate cutting-edge topics like explain ability and privacy-preserving computation into core courses, employing case-based teaching on scenarios such as generative AI ethics deduction and autonomous driving compliance review to shape social responsibility awareness in technological decision-making, ultimately achieving the synchronized enhancement of both technical capabilities and value judgment.

<u>Deepening the Industry–Academia–Research (IAR) Collaborative Talent Cultivation Mechanism</u>.

Guided by industrial demand, it should build an interconnected talent cultivation ecosystem involving application-oriented labs, corporate alliances, and academic communities. Through university–enterprise joint development of hands-on projects like intelligent unmanned systems and Industrial IoT, embedding key technologies like distributed training and model compression into real-world production environments. It should also establish a dynamic credit recognition and transfer mechanism to support student participation in practices such as technical standard formulation and open-source community contributions, and converting these experiences into academic evaluation metrics. Furthermore, a joint academic–industry mentorship system should be introduced, inviting industry experts to co-design an end-to-end curriculum system, and deeply integrate industry elements such as domain-specific datasets and deployment specifications into teaching modules, thereby resolving the structural mismatch between talent cultivation and industrial demands.

Establishing a Dynamic Knowledge Renewal and Ethical Governance Framework.

To address rapid technological iteration, construct an adaptive knowledge system characterized by foundational stability, cutting-edge breakthroughs, and ethical foresight. The foundational tier retains theoretical derivation of classical algorithms while strengthening mathematical logic and systems thinking. The frontier tier dynamically delivers emerging knowledge modules such as quantum machine learning and embodied intelligence via micro-degrees and workshops, ensuring synchronization between instructional content and academic frontiers. The ethical governance tier must establish a full lifecycle assessment mechanism for technologies, embedding training on governance tools like data bias mitigation and synthetic content detection within project practice, to cultivate students' foresight in balancing technological innovation and societal risks.

Enhancing Interdisciplinary Scenario-based Innovation Capabilities.

Centering on vertical domains like smart manufacturing and intelligent healthcare, design compound cultivation pathways of "XAI". Promote cross-disciplinary innovations such as neuromorphic computing and adaptive control through inter-faculty collaborative projects. Offer modular scenario engineering courses, structured around representative real-world problems like industrial defect detection and medical image reconstruction, to cultivate students' capacity for translating demand insights into deployed technologies. Simultaneously construct a three-dimensional evaluation system encompassing technology readiness assessment, scenario compatibility analysis, and social value verification, guiding students to achieve dual breakthroughs in technical feasibility and commercial sustainability within complex systems.

(ii) Scenario Empowerment: Curriculum Design Restructuring via a Dynamic "Technical Competency–Knowledge Unit" Mapping Mechanism

This section aims to optimize existing curriculum design, demonstrating one key application scenario of the multi-source data-driven Intelligent Model for Industry–Research Demand Analysis proposed in this study. The model is capable of quantifying supply–demand relationships and generate corresponding strategies through a structured analytical mechanism, providing scientific decision support for dynamic optimization of the curriculum system, thereby achieving both precise curriculum alignment with industry-research demands and dynamic responsiveness to their evolution.

First, construct a "Technical Competency to Knowledge Unit" mapping rule repository based on derived competency themes and knowledge domains. Then, establish a three-dimensional evaluation matrix comprising academic vitality, industrial demand intensity, and curriculum supply coverage. This matrix facilitates the systematic identification of three types of structural imbalances: technology-declining surplus characterized by high academic output and extensive curriculum coverage but diminishing industrial demand, demand-lagged deficiency marked by strong industrial demand but insufficient course coverage, technology-prospective gap where emerging academic hotspots have yet to be translated into industry roles or integrated into course modules. Subsequently, implement differentiated adjustment strategies targeting the identified outcomes.

For technology-declining surplus modules, adopt credit compression and content migration strategies, transforming redundant credit hours into interdisciplinary elective resources. For demand-lagged deficient domains, build responsive mechanisms featuring industrial technology embedding and systemic case intensification, increasing curriculum time allocation through expanded industry–academia projects and advanced technology modules. Regarding technology-prospective gaps, establish a tiered response system based on technology readiness levels, setting introductory technology units in compulsory courses to establish cognitive frameworks, developing extension projects in practical sessions, forming a scaffolded learning progression from foundational cognition to autonomous exploration and to practical implementation.

This model can be further extended into a closed-loop mechanism encompassing multi-source feedback, three-dimensional evaluation, and adaptive optimization, enabling continuous iteration through educational data feedback, thereby addressing the inherent subjectivity and rigidity of unidirectional open-loop models, thereby establishing a self-correcting decision nexus for talent cultivation. Built upon a triaxial evaluation framework encompassing technology readiness, strategic criticality, and educational compatibility, a dynamic weight regulation module is constructed, consisting of the following components: Technology readiness tracking engine integrates bibliometric analysis and trend prediction outputs, constructs technology lifecycle prediction models to dynamically identify inflection points, and provides data support for knowledge unit curation rules.

A policy-driven weighting mechanism dynamically weights key technology directions extracted from policy text mining, establishes policy sensitivity metrics, and enables annual auto-mapping of regulatory clauses and parameter calibration; Educational feedback adaptor implements self-adaptive adjustments based on learning analytics and competency assessment data, constructs an Educational Compatibility Index, and dynamically adjusts mapping rules via Bayesian networks.

Conclusions

Innovative Contributions

This research transcends the unidimensional optimization constraints inherent in traditional educational studies, constructing the first intelligent model for industry–research demand analysis powered by tri-source (industry–academia–policy) data, with innovations manifesting across three dimensions:

<u>Methodological Innovation</u>: Constructing an Educational Decision-Making Paradigm through Multi-source Data Fusion. A triaxial analytical framework is proposed that integrates recruitment data mining, academic trend forecasting, and policy text analysis, transcending conventional qualitative paradigms. Leveraging LDA topic modeling, co-citation network analysis, and policy keyword extraction to establish a dynamic assessment system of competency requirements, academic trend trajectories, and policy orientation, transforming educational decision-making into computable and verifiable optimization problems, thereby pioneering data-driven pathways for computational pedagogy.

<u>Technological Mechanism Innovation</u>: Designing a Dynamic Closed-loop Responsive System Architecture. A closed-loop architecture is designed, comprising data perception, intelligent decision-

making, and feedback-driven evolution. A custom-built multi-source database is developed to meet industry–research demands. This database enables heterogeneous fusion of unstructured text and structured data via topic modeling, network analysis, and semantic parsing. A dynamic prioritization algorithm ranks educational content based on industrial demand intensity, technological momentum potential, and policy sensitivity, thereby recalibrating competency–to–knowledge mappings. The system further supports dynamic iteration through learning analytics and multi-source updates, enabling curriculum structures to evolve with self-adaptive responsiveness.

Applicational Model Innovation: Reconstructing Deep Industry–Education Synergistic Ecosystems. This model strongly supports the development of data-driven Educational Decision Support Systems by establishing multi-level adaptation mechanisms. At the macro level, it enables the dynamic alignment of national strategies with curricular objectives using model analytics, while prospectively embedding frontier knowledge; At the micro level, it constructs competency–knowledge–course–project mapping repositories, establishing standardized and replicable workflows for demand identification, resource matching, and efficacy validation. Thereby actualizing replicable curriculum optimization pathways and facilitating Smart Education Ecosystem development.

Through integrated innovations in methodology, technological architecture, and application ecosystem, this model catalyzes the intelligent paradigm shift in educational decision-making from experience-driven to data-driven, delivering a systematic solution with theoretical breakthroughs and practical feasibility for coordinated industry–education–research development in the AI era, while resolving structural imbalances in educational supply-side reform.

Limitations and Future Work

Acknowledged limitations currently constrain model performance: Firstly, in terms of data coverage, insufficient sample size and industry representativeness may limit domain generalization capability of demand profiling, particularly risking analytical bias in vertical domains with divergent technology diffusion pathways. Secondly, on the side of technical implementation, the dynamic updating mechanisms still require manual parameter calibration, with real-time semantic parsing and automated matching between demand maps and instructional resources yet unrealized, resulting in response latency when confronting technology emergence.

Future research will proceed along three key trajectories to address current limitations.

1. Data Ecosystem Expansion: Construct a four-dimensional data hypercube extending temporally while covering 10+ key domains horizontally, deeply integrating granular data sources like corporate technical documentation and open-source contribution records to enhance spatiotemporal completeness of demand representation.
2. Differentiated Modeling Advancement: Develop a synergistic analytical framework incorporating firm scale, technological trajectory, and regional policy, developing specialized models including strategy-oriented demand forecasting for industry leaders and technology–adaptation–focused course generators for SMEs, setting policy response coefficients calibrated to regional pilot variations to enhance socio-contextual adaptability.

3. Intelligent Decision-Making Upgrades: Develop an Education Decision Support System prototype integrating the current industry–research analytics model, incorporating knowledge graphs and reinforcement learning techniques to construct dynamic skill–course–position association networks. Real-time crawling of academic resources and job postings enables automated course adjustment recommendations, achieving autonomous closed-loop operation across demand sensing, resource matching, and efficacy evaluation.

Concurrently, a more robust validation framework will be developed across short-, medium-, and long-term horizons. In the short term, track novel metrics like student technical documentation contributions and ethical decision accuracy via course pilots. In the medium term, establish education–employment tracking databases with industry leaders to analyze time-lagged correlations between course modules and job competency. In the long term, construct cross-disciplinary, cross-institutional cohorts applying Difference–in–Differences models to quantify regional innovation density enhancement from talent cultivation paradigm shifts.

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