

A CUI-Based Framework for Dynamic Content Updating and Intelligent Recommendation in an International Trade Innovation Course

*Qing Tang, Jun Yin**

**Corresponding author: Jun Yin*

School of Business, Nanfang College, Guangzhou, 510970, China, yinjl@nfu.edu.cn

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ABSTRACT

The digital transformation of international trade requires university curricula to remain timely, occupationally relevant, and instructionally feasible. This study combines literature analysis, structured secondary analysis of four recruitment reports, and curriculum framework design to examine content updating for a 54-hour International Trade Innovation course for fourth-year undergraduates. Evidence from four recruitment reports issued by Liepin, Randstad, and KOS highlights growing attention to digital skills, cross-border operations, localization, and supply-chain coordination, although demand varies across industries and job functions. Based on labor-market evidence, course objectives, and teaching constraints, the study develops a Curriculum Update Index (CUI) covering frontier relevance, industry demand, job relevance, curriculum alignment, and instructional feasibility. A human-in-the-loop framework links trusted data sources, AI-assisted topic identification, CUI assessment, rule-based recommendations, and teacher review. Six candidate topics illustrate the recommendation process and curriculum adjustment under the fixed allocation of 36 theoretical and 18 practical hours. The numerical example demonstrates framework operability rather than an empirical ranking or evaluation of learning outcomes. The framework provides an interpretable and auditable approach to continuous curriculum updating in digital trade education.

1. Introduction

1.1 Research Background

Artificial intelligence (AI) and digital technologies are reshaping how international trade connects markets and organizes business processes. Research by the World Trade Organization (WTO, 2024, 2025) suggests that AI may affect trade

by reducing transaction costs, increasing productivity, and improving information processing, while simultaneously creating challenges related to data governance and regulatory coordination. UNCTAD (2025) likewise emphasizes that the benefits of technological development depend strongly on infrastructure, data, and skills.

In labor economics, large-scale online job advertisements have become an important high-frequency and traceable source for observing changing skill requirements. Deming and Kahn (2018) show substantial variation in firms' skill requirements even within finely defined occupations, while Acemoglu et al. (2022) find that growth in AI-related vacancies is concentrated in establishments whose task structures are compatible with relevant technologies and is accompanied by changes in skill requirements elsewhere. These findings provide a methodological basis for using recruitment evidence to inform curriculum updating.

1.2 Curriculum Updating Problem

International Trade Innovation covers digital trade in services, cross-border data flows, platform operations, digital marketing, digital payments, and smart logistics. Its knowledge base changes quickly and is closely tied to business scenarios. Conventional curriculum revision, which relies mainly on periodic textbook and syllabus updates, often struggles to incorporate new information dispersed across industry reports, corporate practice, and labor markets.

At the same time, new technologies cannot simply be added without considering students' prior knowledge, course objectives, and limited contact hours. Treating information popularity as equivalent to instructional value risks content accumulation and fragmentation, weakening the internal relationship between foundational knowledge and business logic.

1.3 Policy and Educational Context

China's Action Plan for “AI + Education,” jointly issued by the Ministry of Education and four other departments, provides a policy context for integrating AI into teaching and knowledge-system development (Ministry of Education et al., 2026). Internationally, UNESCO's AI Competency Framework for Students similarly advocates embedding AI learning objectives within existing disciplinary curricula

while placing critical judgment and ethical awareness at the center of competency development (UNESCO, 2024). For international trade education, AI can therefore contribute not only by generating teaching materials but also by helping identify knowledge changes and map them to educational objectives. Curriculum updating requires a mechanism that translates external demand signals into internal content configurations so that new content is both evidence-based and coherent with the existing knowledge structure.

1.4 Research Objectives and Scope

This study focuses on a 54-hour International Trade Innovation course for fourth-year undergraduates, comprising 36 theoretical and 18 practical hours. It addresses three progressive questions: how candidate topics can be identified, how their curricular value can be evaluated, and how limited teaching hours can be reallocated. Recruitment reports are used to analyze occupational demand and competency preferences, after which a Curriculum Update Index (CUI) is constructed to support evidence-constrained recommendations. The purpose is to propose an analytical framework and an application scheme rather than to evaluate an already implemented teaching intervention. Because the course is designed primarily to prepare fourth-year undergraduates for entry-level positions in domestic Chinese foreign-trade and cross-border e-commerce firms, the recruitment evidence is restricted to positions and competencies reflected in China's domestic labor market; overseas expatriate positions are excluded.

2. Literature Foundation and Research Methods

2.1 Curriculum Knowledge Analysis and Content Updating

A systematic review indicates that AI research in higher education has long been dominated by computer science and STEM fields, with comparatively limited substantive participation by education researchers; integrated frameworks that combine technical feasibility with pedagogical logic remain underdeveloped (Zawacki-Richter et al., 2019). Recent work has explored AI for curriculum analysis through knowledge extraction and relationship modeling. Gacek and Adrian (2025)

use large language models (LLMs) to extract core concepts and prerequisite relationships from syllabi and construct knowledge graphs for curriculum analysis. Abu-Rasheed et al. (2025) connect curriculum and domain models to support personalized learning-path recommendations. Reales et al. (2024) combine LLMs and knowledge graphs to identify core concepts in educational resources.

These studies establish technical foundations for processing unstructured curricular information, but curriculum recommendation must also connect knowledge relationships with specific teaching contexts. Tyler's (1949) curriculum rationale requires content selection to follow educational objectives and the organization of learning experiences, while constructive alignment requires consistency among learning outcomes, teaching activities, and assessment tasks (Biggs, 1996). Thus, any new topic should have an explicit place at the levels of objectives, activities, and assessment rather than merely being appended to a knowledge list.

Compared with analysis of internal curriculum structures, an international trade innovation course faces the additional challenge of rapid external knowledge change. WTO research on the long-run trade effects of digitalization places AI adoption, online sales, remote interaction, trade costs, and data policy within a common analytical framework (Bekkers et al., 2025), illustrating the systemic links among technology, business, and rules. Curriculum updating should therefore evaluate not only novelty but also industrial application, occupational relevance, and instructional fit. AI literacy can be organized into four dimensions, knowing and understanding, using and applying, evaluating and creating, and ethical issues (Ng et al., 2021)—which helps define the appropriate depth of AI-related course content. The CUI proposed here integrates external demand with internal instructional conditions to address limitations of recommendations based only on semantic similarity or topic frequency.

2.2 Data Sources and Analytical Procedures

The evidence base consists of trade statistics, recruitment trend reports, authoritative frontier materials, publicly documented corporate cases, and institution-specific curriculum files. Trade statistics are drawn from China's Ministry

of Commerce for 2024-2025 (Ministry of Commerce, 2025, 2026), while the definition of digital trade follows the Handbook on Measuring Digital Trade (IMF et al., 2023). Recruitment evidence includes Liepin's Q1 and Q2 2025 recruitment trend reports, Randstad's 2025 recruitment white paper, and KOS's 2026 talent-market trend report. All four concern the Chinese domestic recruitment market; items involving overseas expatriate positions are excluded. Frontier materials prioritize WTO, UNCTAD, and Ministry of Commerce publications, while industry cases are restricted to materials for which the company, application scenario, and public source can be traced. Institution-specific materials include the training program, syllabus, existing modules, and task requirements.

Recruitment reports were selected according to three criteria: publication within the 2025-2026 curriculum-revision window; inclusion of information on occupations, functions, competencies, or talent shortages; and identifiable source organizations, statistical periods, and data definitions. The unit of analysis is a traceable “occupation/function – competency requirement – business scenario” information unit. Original values, periods, respondents, and page numbers were recorded before information was classified into five functional categories: marketing, cross-border operations, logistics and supply chain, payments and finance, and compliance and risk control. Each item was then mapped to the course topics it could support. Percentages from different reports were not pooled, and duplicated data released by the same organization were retained only once. Because the evidence base is limited, the procedure is described as structured secondary-data analysis rather than statistical content analysis of a large corpus of job advertisements.

AI serves as an identification aid rather than an autonomous decision maker. The proposed workflow includes webpage update tracking, text cleaning, topic and entity extraction, semantic clustering, trend alerts, and candidate-topic consolidation. For auditability, the system retains the source organization, title, publication date, collection date, URL, abstract, and topic tags. Candidate topics are grouped into new technologies, new business forms, new models, new rules, and new occupational skills before entering CUI assessment. All recommendations require review by the

teaching team before becoming formal course content. The governing principle is therefore: AI discovers, CUI filters, and teachers decide. The present study demonstrates rules and illustrative calculations; it does not claim to have deployed a fully automated recommendation system.

3. Changes in Talent Demand and Their Curricular Implications

3.1 Service-Trade Development as a Context for Curriculum Updating

According to the Ministry of Commerce, China's total trade in services reached RMB 8,082.31 billion in 2025, an increase of 7.4% year on year. Trade in knowledge-intensive services reached RMB 3,087.95 billion, up 6.6% (Ministry of Commerce, 2026). Compared with 2024, both categories continued to expand, although at different rates (Table 1). This structural divergence provides a macroeconomic context for discussing business opportunities in services trade and for strengthening students' ability to interpret structural differences and statistical definitions. Macroeconomic scale provides context; specific curriculum updates still require business- and competency-level evidence.

Table 1. China's Trade in Services, 2024–2025

Indicator	2024	YoY (%)	2025	YoY (%)
Total trade in services	75,238.0	14.4	80,823.1	7.4
Services exports	31,755.6	18.2	36,267.9	14.2
Services imports	43,482.4	11.8	44,555.1	2.5
Knowledge-intensive services trade	28,965.2	6.5	30,879.5	6.6
Knowledge-intensive services exports	16,573.2	7.4	18,321.2	10.5
Knowledge-intensive services imports	12,392.0	5.4	12,558.3	1.3

Note. Amounts are RMB 100 million. Sources: Ministry of Commerce (2025, 2026). Published year-on-year rates are retained. The 2025 export and import components differ from the published total by RMB 0.1 × 100 million because of rounding. Knowledge-intensive services trade and digitally deliverable services trade are distinct statistical categories.

3.2 Structural Characteristics of Domestic Foreign-Trade Job Demand

Because the target students mainly enter domestic foreign-trade and cross-border e-commerce firms, occupational evidence is interpreted with reference to job demand

and talent shortages within China.

Liepin's Q1 2025 job-demand chart reports that foreign-trade specialists/assistants accounted for 0.63% and cross-border e-commerce operations positions for 0.56% of the top 30 positions by employer demand. Corresponding Talent Shortage Index (TSI) values were 2.91 for foreign-trade managers/supervisors, 3.06 for cross-border e-commerce operations, and 5.98 for freight-forwarding sales (Liepin Big Data Research Institute, 2025b, pp. 12, 15). Although the two demand shares were below 1%, their TSI values were well above 1, indicating that these foreign-trade-related occupations represent relatively small segments but remain in shortage under the report's definition. The combination of limited scale and persistent shortage suggests that curriculum updating should be justified by changes in competency structure rather than by simple expansion in job numbers. TSI indicates labor-market tightness as defined by the report and should not be converted directly into teaching-hour priorities.

Table 2. Domestic Foreign-Trade Job Demand and Talent Shortage Indicators

Data item	Reported value	Period/source location	Interpretation
Foreign-trade specialist/assistant	0.63%	2025 Q1; Liepin Q2 report, p. 12	Share among top-30 positions by employer demand; not an AI-skill share.
Cross-border e-commerce operations	0.56%	2025 Q1; Liepin Q2 report, p. 12	Position-demand share in the same chart; cannot be extrapolated to national headcount.
Foreign-trade manager/supervisor	TSI 2.91	2025 Q1; Liepin Q2 report, p. 15	Talent shortage index, not a percentage or growth rate.
Cross-border e-commerce operations	TSI 3.06	2025 Q1; Liepin Q2 report, p. 15	TSI > 1 denotes excess demand under the report's definition.
Freight-forwarding sales	TSI 5.98	2025 Q1; Liepin Q2 report, p. 15	Supports links to logistics and customer development; not a teaching priority score.

Note. Source: Liepin Big Data Research Institute (2025b). Only course-relevant items directly corresponding to domestic Chinese foreign-trade positions are included.

At the task level, these occupations can involve market-information organization, customer development, platform-content maintenance, order follow-up, logistics fulfillment, and customer maintenance. Because the recruitment reports do not provide a complete task-level census, these examples are used as instructional

mappings rather than population-level estimates of job-task frequency. These functions are sequentially linked along the business chain. Digital marketing should therefore be taught in connection with market selection, customer demand, transaction conversion, and supply-chain response rather than as content production alone. For fourth-year undergraduates, these tasks closely resemble the entry-level responsibilities they may assume after graduation and thus have clear instructional value.

3.3 Integrating Digital and International Competencies

In Randstad's survey, 29% of respondents expected their organizations to concentrate recruitment in 2025 on information-technology talent related to digital transformation and AI, while 27% identified marketing and sales development. Regarding candidate preferences, 25% selected digital and intelligent skills, 22% innovation and problem-solving, and 11% international perspective and language competence (Randstad, n.d., pp. 10, 20). These two sets of indicators refer to different survey questions—recruitment functions and competency preferences—and therefore cannot be added to produce an “AI job share.” They nevertheless indicate simultaneous attention to technology use and business understanding. This pattern broadly aligns with cross-border e-commerce talent models that combine technical skills, analytical capacity, and business practice (Cheng et al., 2019).

Table 3. Recruitment Priorities and Competency Preferences in the Randstad Survey

Indicator category	Item	Value	Source
Expected priority recruitment functions in 2025	Technology R&D and innovation	41%	Randstad, p. 10
Expected priority recruitment functions in 2025	Digital transformation, AI, and other IT	29%	Randstad, p. 10
Expected priority recruitment functions in 2025	Marketing and sales development	27%	Randstad, p. 10
Candidate preference	Digital and intelligent skills	25%	Randstad, p. 20
Candidate preference	Innovation and problem-solving	22%	Randstad, p. 20
Candidate preference	International perspective and language competence	11%	Randstad, p. 20

Note. The survey was completed in September 2024 with 1,790 respondents overall; valid responses for each individual item were not separately reported. Recruitment functions and competency preferences are different questions.

KOS's outlook for China's 2026 consumer-goods talent market further

emphasizes that cross-border business positions in domestic firms must consider supply-chain conditions, target-market culture, local regulation, and social-media environments, with particular attention to data analytics, localized cross-border marketing, and sustainable supply-chain capabilities (KOS, n.d., pp. 31 – 32). Combined with the recruitment evidence, this suggests that AI tools should be situated within international business contexts. Students need to understand the data, objects, and conditions on which AI outputs depend rather than merely learning operating procedures. This corresponds more closely to the “evaluating and creating” and “ethical issues” dimensions of AI literacy than to “using and applying” alone (Ng et al., 2021).

The evidence supports integrating digital capabilities with market development, localization, and supply-chain coordination, but it does not establish that any single AI skill has become a universal requirement across all foreign-trade jobs. AI-related job growth is selective across establishments and tasks, and its observable short-run effect on aggregate employment structures remains limited (Acemoglu et al., 2022). Requirements reported for mid- and senior-level roles should likewise not be transferred directly into undergraduate learning outcomes. Fourth-year students commonly begin with documentation, customer development, or platform operations; course objectives should therefore target entry-level tasks rather than the complete competency profile of senior managers.

4. Construction of the Curriculum Update Index

4.1 Five-Dimensional Evaluation Logic and Indicators

Recruitment demand can signal the need for content updating, but occupational relevance is not equivalent to curricular admissibility. The CUI contains five dimensions: frontier relevance (F), industry demand (I), job relevance (J), curriculum alignment (R), and instructional feasibility (T). F captures the level and change of attention to a topic in authoritative sources; I reflects identifiable business applications; J measures support for competency demand in recruitment evidence; R

evaluates alignment with program objectives, course outcomes, task outputs, and module structure; and T reflects prerequisites, teaching resources, and available hours. The five first-level dimensions are equally weighted, while the secondary indicators are equally weighted within each respective dimension. This choice prioritizes transparency and interpretability and should not be understood as a weight structure validated by a large sample.

$$CUI_k = \frac{F_k + I_k + J_k + R_k + T_k}{5}$$

Table 4. Indicator System for the Curriculum Update Index

Dimension/indicator	Operational definition and scoring	Scope/conditions
F1 Current attention	100 × documents containing topic / valid documents	Fixed WTO, UNCTAD, and Ministry of Commerce sources; duplicate topic mentions in one document counted once.
F2 Change in attention	Normalize adjacent-period change in topic share to 0–100	Scale determined by candidate-topic distribution; no fixed 10-percentage-point ceiling.
F3 Repository novelty	Score by when the topic first enters the observation repository	Repository novelty only; not a claim of global novelty.
F4 Source coverage	100 × independent supporting organizations / 3	Syndicated copies are not double-counted.
I1 Case coverage	100 × firms involving topic / firms in valid case library	Describes the case library; not an industry adoption rate.
I2 Application maturity	100 × mean case maturity / 3	0 concept; 1 trial; 2 partial application; 3 stable process.
I3 Scenario coverage	100 × evidenced business links / 8	Research, development, marketing, transaction, payment, logistics, risk control, compliance.
J1 Cross-organization support	100 × organizations explicitly supporting topic demand / 3	Multiple reports from one organization count as one organization.
J2 Functional coverage	100 × directly related functional categories / 5	Marketing, cross-border operations, logistics/supply chain, payments/finance, compliance/risk.
J3 Evidence strength	0, 25, 50, 75, or 100	None, qualitative outlook, qualitative retrospective, survey intention, observed job statistics; sensitivity analysis required.
J4 Description completeness	25 points each for occupation, competency, scenario, and task/output	All elements must come from one traceable description.
R1 Program relevance	0–100 for direct relation to program objectives	Quote the original program objective and explain the relationship.
R2 Course-outcome support	100 × directly supported outcomes / total outcomes	Explain how the topic task supports each outcome.

R3 Task/assessment measurability	25 points each: output, rubric, evidence requirement, feedback	Avoid adding a topic name without an assessable task.
R4 Module articulation	25 points each: prerequisite, insertion point, boundary, module link	Missing records are not treated as satisfied.
T1 Prerequisite coverage	100 × covered prerequisite points / all required points	Explicitly record when no prerequisites are required.
T2 Resource readiness	25 points each: case, data, tool, assessment criteria	Resources must be accessible, sourced, and instructionally appropriate.
T3 Hour fit	Assessed from replaceable hours relative to required hours	Theory and practice hours are checked separately.

4.2 Missing Data, Weighting, and Robustness

After a complete search, an indicator receives 0 when no supporting evidence is found; an indicator that has not yet been collected or cannot be judged is recorded as missing. No formal ranking is produced when any required indicator is missing. The composite score organizes evidence rather than replacing educational judgment, and essential foundational content is not automatically removed because of a low score.

Equal weighting is the primary analysis. Entropy weighting is used only as a robustness comparison and is not treated as a direct measure of educational importance. The entropy-weighted specification is treated as an alternative weighting structure for robustness analysis and therefore does not preserve the equal 20% weights assigned to the five first-level dimensions in the baseline model. When the number of candidate topics and data completeness are sufficient, entropy weights may be calculated for the 18 secondary indicators and aggregated into the five dimensions. For normalized score x_{ij} , the calculations are:

$$p_{ij} = \frac{x_{ij}}{\sum_i^m x_{ij}}$$

$$e_j = -\frac{1}{\ln m} \sum_i^m p_{ij} \ln p_{ij}$$

$$d_j = 1 - e_j$$

$$w_j = \frac{d_j}{\sum_j^n d_j}$$

Zero terms are treated as zero in the entropy calculation, while all-zero or constant columns provide no discriminatory information.

Robustness analysis compares equal-weight and entropy-weight results using

Spearman rank correlation, top-K overlap, and changes in recommendation categories. It also includes leave-one-organization-out tests, alternative scoring for J3, and changes to the observation window. Because entropy weights reflect sample dispersion rather than educational importance, substantial disagreement between weighting schemes must be resolved by returning to the underlying evidence and course objectives.

4.3 Illustrative Calculation and Recommendation Rules

To show how the framework produces actionable recommendations, six candidate topics directly related to the existing course are used in an illustrative calculation. The scores in Table 5 are hypothetical inputs that assume indicator coding has already been completed. Their sole purpose is to demonstrate composite calculation, threshold decisions, and corresponding curriculum actions; they are not empirical findings. Formal calculation requires a source-level evidence record for every indicator in Table 4 and complete case, recruitment, and institutional curriculum data.

Table 5. Illustrative CUI Calculation Using Hypothetical Inputs

Candidate topic	F	I	J	R	T	CUI	Recommendation
Generative AI-assisted international market research	90	82	76	92	88	85.6	Priority strengthening
Cross-border data flows and rule verification	86	70	64	94	84	79.6	Integrate as special topic
Localized cross-border e-commerce operations	78	82	84	90	88	84.4	Priority strengthening
Smart logistics and overseas-warehouse coordination	74	84	86	86	84	82.8	Priority strengthening
Digital payments and digital currency	80	76	70	84	80	78.0	Integrate as special topic
AI-assisted supply-chain risk identification	82	70	66	80	74	74.4	Integrate as special topic

Initial thresholds are set as follows: 80 or above, priority strengthening; 70 to below 80, integration as a special topic; 60 to below 70, observation/extension; and below 60, no new addition in the current cycle. Routine additions must also satisfy the course-fit conditions and fit separately within theoretical and practical hours. These thresholds are provisional rules requiring validation rather than universal admission

criteria. Under the hypothetical inputs, localized operations, smart-logistics coordination, and generative-AI-assisted market research would receive priority strengthening, while the other three topics would be integrated as special topics. This demonstrates how the rules operate; it does not establish their empirical priority.

5. Intelligent Recommendation and Curriculum Application

5.1 Human-in-the-Loop Recommendation Process

The recommendation process contains six stages. First, establish a trusted-source list covering WTO, UNCTAD, the Ministry of Commerce, industry reports, corporate cases, recruitment materials, and institutional curriculum files. Second, use webpage update detection, text cleaning, topic extraction, entity recognition, semantic clustering, and trend alerts to identify new or changing information. Third, consolidate this information into candidate topics under five categories: new technologies, new business forms, new models, new rules, and new occupational skills. Fourth, calculate the five CUI dimensions while displaying the original evidence and missing items. Fifth, combine the composite score, curriculum-fit conditions, and relationships with existing content to generate recommendations such as add, strengthen, integrate, retain, compress, replace, or observe. Sixth, the teaching team reviews both the recommendation and its evidence before deciding whether the item enters the course knowledge base and the next syllabus revision.

AI output must not serve as a direct basis for curriculum revision. Each recommendation should display its source, date, business scenario, related learning outcomes, content proposed for replacement, and required hours so that teachers can trace the reasoning. When sources conflict, information is insufficient, or rules are unclear, the system should return only a “verification required” flag rather than a formal recommendation.

5.2 Curriculum Restructuring Under Contact-Hour Constraints

Drawing on the competency directions indicated by the recruitment reports and the rule demonstration in Table 5, the curriculum scheme shows how generative-AI-assisted market research, localized cross-border e-commerce operations,

and smart-logistics coordination can be embedded in existing modules. New content must be accommodated through internal module restructuring. The 54-hour allocation in Table 6 is an illustrative curriculum configuration developed through teacher judgment under the CUI recommendations and fixed-hour constraints. It is not a mechanical conversion of recruitment percentages and is not “proven” by the hypothetical scores.

Table 6. Proposed Allocation of Hours for International Trade Innovation

Course module	Theory	Practice	Total	Adjustment rationale/task emphasis
Foundations of international trade innovation and digital trade	4	2	6	Retain essential concepts and statistical definitions.
Digital trade in services and cross-border data flows	5	2	7	Strengthen rule verification and data-governance analysis.
Cross-border e-commerce and localized operations	5	3	8	Strengthen localization, platform operations, and market adaptation.
Digital marketing and generative-AI-assisted market research	5	3	8	Embed source verification, customer analysis, and AI-use records.
Digital payments and fintech	4	2	6	Integrate digital payment/currency developments while retaining transaction logic.
Smart logistics, overseas warehouses, and supply-chain coordination	5	3	8	Strengthen fulfillment design and cross-border coordination.
Trade compliance and AI-assisted risk identification	4	1	5	Integrate rule checking and risk-identification tasks.
Integrated cross-border business project	4	2	6	Connect marketing, transaction, payment, logistics, and compliance decisions.
Total	36	18	54	Theory and practice hours remain fixed.

If a module originally contains theoretical hours and practical hours, and the corresponding adjustments are defined separately, the revised plan must satisfy the following conservation constraints:

$$\sum_i (H_i T + \Delta H_i T) = 36$$

$$\sum_i (H_i P + \Delta H_i P) = 18$$

Separate conservation of theoretical and practical hours ensures that every addition or strengthening action has an explicit location for compression, replacement, or integration rather than creating hidden extra workload outside the stated 54 hours.

5.3 Alignment of Objectives, Activities, and Assessment in Business Tasks

Consider the task “Generative-AI-assisted target-market research.” Students investigate the entry of a specified product into a target market by conducting

information retrieval, competitor comparison, customer-demand analysis, and marketing-plan design. AI may assist in summarizing information, generating search leads, and proposing alternative expressions, while students remain responsible for checking sources, identifying statistical definitions, judging conditions of applicability, and explaining target-market differences. Final outputs include a market brief, a source list, prompts and AI-use records, and a reflective statement. Assessment criteria address evidence quality, business analysis, plan feasibility, responsible AI use, and communication quality, thereby maintaining alignment among course outcomes, learning activities, and assessment evidence (Biggs, 1996).

The task operationalizes the recruitment evidence on digital skills and market development and converts localization competency into an activity appropriate for fourth-year undergraduates. Platform operations, logistics, and payment modules can share the same product-and-market scenario, allowing marketing judgments, transaction arrangements, and fulfillment plans to form a continuous business chain.

6. Discussion and Conclusion

6.1 Findings and Teaching Implications

The curricular value of recruitment reports lies not in directly determining teaching hours but in revealing changes in occupational tasks and competency structures. Domestic foreign-trade positions account for a limited share of total job demand yet coexist with relatively high talent-shortage indicators. Curriculum updating should therefore focus on competency restructuring within existing occupations rather than interpret localized trends as universal requirements. Digital skills become instructionally meaningful when connected with market development, localized operations, supply-chain coordination, and rule verification and translated into business tasks appropriate for undergraduates.

The CUI places external knowledge change, industrial application, occupational demand, and internal instructional conditions within one evaluation structure. Its principal function is to organize evidence, expose missing information, and create discussable reasons for recommendations rather than replace the judgment of the

teaching team. The illustrative calculation links candidate topics, recommendation categories, and contact-hour allocation, while also showing that some frontier topics can be embedded within existing modules rather than continuously added as new chapters. In this human–AI division of labor, AI supports incremental discovery and semantic organization, the CUI provides structured screening, and teachers make judgments concerning learning outcomes, disciplinary coherence, and educational requirements that cannot be fully quantified.

6.2 Limitations and Future Validation

The study has four main limitations. First, recruitment evidence comes from four secondary reports with different periods, populations, and methods and therefore cannot be pooled into a national estimate of job demand. Second, the illustrative calculation does not yet incorporate a large corpus of job advertisements; the J dimension mainly reflects support across institutional reports rather than the frequency of skills in job postings. Third, CUI weights, score levels, and thresholds are initial rules. Although a sensitivity-analysis plan is specified, expert review and a larger sample of topics are still required. Fourth, the proposed curriculum has not yet been evaluated over successive teaching cycles, so no inference can be made that student competencies have already improved.

Future work should proceed through data expansion, rule validation, teaching implementation, and outcome evaluation. Subject to platform rules, researchers can supplement the evidence base with public job advertisements or manually sampled records, expand the corporate-case library and frontier-material observation window, invite curriculum, industry, and educational-technology experts to assess content validity, compare equal, expert-derived, and entropy weights, and finally evaluate appropriateness through student work, course performance, and learning feedback. For other institutions and courses, the CUI should be recalibrated to local program objectives and contact-hour structures rather than copying the thresholds used here.

6.3 Conclusion

This study develops a dynamic content-updating and recommendation framework for an International Trade Innovation course. The framework uses trusted

sources to detect knowledge change, AI to assist candidate-topic identification, and the CUI to evaluate frontier relevance, industry demand, job relevance, curriculum alignment, and instructional feasibility. Teachers then decide whether to add, strengthen, integrate, compress, or replace content under the fixed 54-hour constraint. The six-topic numerical demonstration shows how external information can be converted into traceable curriculum recommendations while preserving the 36-hour theory and 18-hour practice structure. The contribution is an interpretable and auditable human-in-the-loop tool; its effectiveness remains to be validated through empirical scoring with real data and subsequent teaching practice.

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