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From Integration to Impact: Constructing a Predictive Evaluation Model for AI's Penetration Effect in Vocational Construction Education

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Abstract: Artificial intelligence is reshaping vocational education, but few instruments exist for measuring how deeply AI has actually penetrated a curriculum. This paper combines CiteSpace bibliometric analysis of the CNKI, Web of Science, and Scopus literature with a questionnaire survey and a case study of Sichuan College of Architectural Technology to construct the AI-Vocational Education Index (AI-VEI), a twelve-indicator model that converts AI penetration into a single score. Indicator selection is anchored in bibliometric hotspots and policy priorities rather than in expert opinion alone; weights are derived from a multi-criterion layered fusion of keyword count, burst strength, and betweenness centrality, and are then combined with Analytic Hierarchy Process weights (consistency ratio 0.095) to balance data objectivity with expert judgment. Applied to the case college, the model returns a score of 62 out of 100, corresponding to grade C on the four-band scale adopted here. The survey identifies four persistent gaps: 16.7% of respondents have never used an AI educational tool; AI remains absent from systematic curriculum design; acceptance and skills training remain weak, with 80% of respondents fearing erosion of independent thinking; and generative-AI tools are almost entirely missing from school-enterprise practice bases. The study contributes a transparent, reproducible instrument for evidence-based decisions about AI in vocational education, and argues that policy targets should be set against measured penetration rather than against nominal adoption.

Keywords: Vocational education; Artificial intelligence; Educational reform; CiteSpace; AI-Vocational Education Index; Combined weighting

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1. Introduction

Vocational education in China is being asked to reinvent itself at the same time as the industry it serves is contracting. The 2013 Decision on Several Major Issues Concerning Comprehensively Deepening Reform set the overall direction for education reform, and the 2022 Opinions on Deepening the Reform of the Modern Vocational Education System called for a multi-form, multi-channel, and sustainably developmental ladder

system aligned with market demand and industrial structure [1–3]. Artificial intelligence has entered this debate as both a subject and a tool: large models such as DeepSeek, DouBao, Kimi and WenXinYiYi have moved into everyday use, and AI is widely described as triggering a productivity revolution in knowledge. Exploring how these models change teaching, and how their implementation can be promoted, is therefore a research question with immediate practical stakes [4].

The stakes are unusually high for construction-related programs. Grey-forecasting work suggests that the employment elasticity of China's construction industry will approach zero on a five-year moving average, so that output growth will exert a diminishing pull on employment over the coming decade [5]. Graduate destination data confirm the pressures: in 2024 only 6.7% of four-year college graduates entered construction, 2.3 percentage points below 2020 and the second-largest decline of any industry, with the Engineering Cost program third from the bottom on destination fulfillment [6]. Among three-year vocational graduates, the picture is similar: destination fulfillment for construction majors stood at 89.3% six months after graduation, but only 8.8% actually entered the sector, down 2.6 percentage points from 2020 [7]. Field visits to colleges in Sichuan and interviews with construction-program teachers suggest the real situation may be worse still. Programs that once guaranteed a trade now have to justify themselves, and AI is increasingly presented as part of the answer.

International evidence on the demand side is consistent with this reading. A survey of 111 undergraduates found that students are highly aware of the potential benefits of generative AI and support its integration into the curriculum, and labor-market evidence indicates that AI skills command a wage premium of around 23% while the return to formal degrees in AI-intensive occupations is comparatively low [8–9]. Classroom trials of AI-supported writing and argumentation tools report broadly positive perceptions, although evidence from emergency remote teaching cautions that technology alone does not improve outcomes without adequate support [10–12]. If employers are moving towards skill-based hiring, vocational colleges that fail to embed AI risk graduating students into a market that no longer recognizes their qualifications.

Despite this, the literature offers little guidance on how to measure whether AI has actually entered a program. Existing studies document applications, debate governance, and describe national reform strategies, but they stop at describing whether AI is present rather than how deeply it penetrates teaching, assessment, and practice. This study addresses that gap [13–15]. Its contributions are threefold: it maps what the domestic and international literatures actually attend to; it documents, through a case study and a survey, where AI implementation currently falls short; and it constructs a quantitative instrument, the AI-VEI, that turns penetration into a measurable score. Four questions organize the work: (1) what does research on AI in education reform currently attend to, domestically and internationally; (2) what has been implemented in vocational institutions and with what results; (3) how can AI-integrated teaching be evaluated systematically across institutions; and (4) what should institutions prioritize next.

2. Methodology

The study combines bibliometric analysis, a questionnaire survey, and an institutional case study. Bibliometric analysis using CiteSpace establishes what the field attends to and supplies the quantitative anchors from which the evaluation indicators are later derived; the questionnaire and the case study supply the practical and perceptual evidence needed to judge what can realistically be measured.

Domestic literature was retrieved from CNKI using two Chinese keyword pairs, "artificial intelligence" + "educational reform" and "vocational education" + "reform", over the window 13 April 2021 to 13 April

2025. The first pair returned 2,124 documents and the second 20,966. Domestic sources were restricted to authoritative indexes (PKU Core, AMI, CSSCI, WJCI, CSCD). International literature was retrieved from Web of Science and Scopus using "vocational" + "AI"; WOS returned 77 documents and Scopus 3,477, of which the top 500 were screened and Chinese publications excluded, leaving 312. The 389 international documents (77 + 312) were analyzed together, and a further WOS search on "vocational education" + "reform" returned 623 documents used to identify leading countries and research directions. Because the retrieval window closes in April 2025, counts for 2025 are partial and are interpreted as such throughout.

The empirical component is a case study of Sichuan College of Architectural Technology, a representative architecture-focused vocational college in Sichuan that began integrating AI comparatively early. Documentary evidence on curriculum reform, faculty development, and school-enterprise collaboration was collected from the college, and a questionnaire captured teachers' and students' experience of, and willingness to engage with, AI tools. The questionnaire was completed by 42 respondents (21 teachers and 21 students); item-level denominators vary slightly because of missing responses, and all percentages below are reported against the respondents who answered that item.

The AI-VEI is assembled in three stages. Candidate indicators are drawn from the intersection of bibliometric hotspots, observed practice, and survey findings, so that every indicator traces to either a research frontier or a documented practical need. Objective weights are derived from the bibliometric statistics attached to each indicator and subjective weights from an Analytic Hierarchy Process exercise with college experts and leaders. The two are combined and applied to the case college as a worked example.

3. Results

3.1. Domestic research on vocational education reform

Publication counts on vocational education reform rose, fell, and then rose again over the window: 4,720 articles in 2021 followed by a gentle decline to a low of 3,288 in 2024, with 2021 as the peak. The decline in 2024 is notable because 2024 was the year in which AI models and applications became widely available; the partial 2025 count points upward again. Overall, 4,723 articles—22.5% of the 20,966 retrieved—meet the high-quality index criteria used here. Keyword counts are dominated by "higher vocational colleges" (2,358), followed by the "1+X certificate system" (1,301), "integration of industry and education" (1,201) and "educational reform" (929), with "vocational colleges" (748), "talent cultivation" (686), the "three-teach reform" (583) and "high-quality development" (555) completing the picture. The hotspot structure is therefore institutional and policy-driven: research concentrates on how colleges should be organized and certified rather than on what happens inside classrooms.

The ten most prolific authors publish at consistently high quality—four of them at 100%—and are affiliated mainly with research universities rather than vocational colleges [16–24]. Their recommendations cluster into three groups. On high-quality development, the emphasis is on shifting from individual specialties to professional clusters, with policy design at the macro level, digital industrial transformation at the meso level, and core institutional capability at the micro level [16–17]; several authors additionally press for big data, AI, cloud services, and virtual reality to enter teaching through smart tools and flipped classrooms [18]. On school-enterprise cooperation, proposals range from a community of shared interest between schools and enterprises to city-level consortia with government-led coordination, incentive and supervision mechanisms [19–22]. On teaching models, the recurring themes are "dual-qualified" staff and an integrated teaching-

learning-assessment model with differentiated support [23–24].

3.2. International research on vocational education reform

International output is smaller, so the analysis focuses on cluster structure. Nine keyword clusters emerge, among which education policy, mental health and curriculum negotiation are prominent, and the Republic of Korea, Switzerland and Russia are the most frequently referenced national contexts. Seven keywords recur consistently—work, average, education, capitalism, policy, skills and curriculum—with the highest burst strength in education (1.63), work (1.21) and skills (0.99); skills and curriculum have retained strong momentum since 2023. Institutionally, the field is fragmented, although UCL, LSE and the University of Turin form a comparatively tight collaborative network in Europe.

Two findings matter for the present study. First, the international literature treats vocational education reform as an economic and policy problem at least as much as a pedagogical one, which is consistent with the domestic emphasis on industry-education integration. Second, where technical content is specified, it is surprisingly concrete: proposals for vocational students include object tracking, region-of-interest selection, single and multiple object tracking, evaluation metrics, motion prediction, classification and deep neural networks [15]. These are transferable AI competences rather than generic digital literacy, and they foreshadow the emphasis on measurable skills that the AI-VEI model adopts.

3.3. Research on AI in education reform

Literature specifically on AI in education reform is scarce, particularly internationally, so the analysis again rests on keyword structure. In the CNKI corpus, ten clusters appear; excluding those that merely restate the search terms, eight are substantive, covering curriculum reform, higher education institutions, talent training, new-era engineering and integrated development. Among the strongest burst terms are Statistics (2.96), Informationization (2.69), Higher Education (2.56) and the Intelligent Era (2.51), with Deep Learning (1.81) and Technology Empowerment (1.66) bursting later, in 2022–2023 (**Figure 1**). The pattern suggests that domestic work has moved from general digitalization towards specific AI techniques, but has not yet settled on how those techniques enter a curriculum.

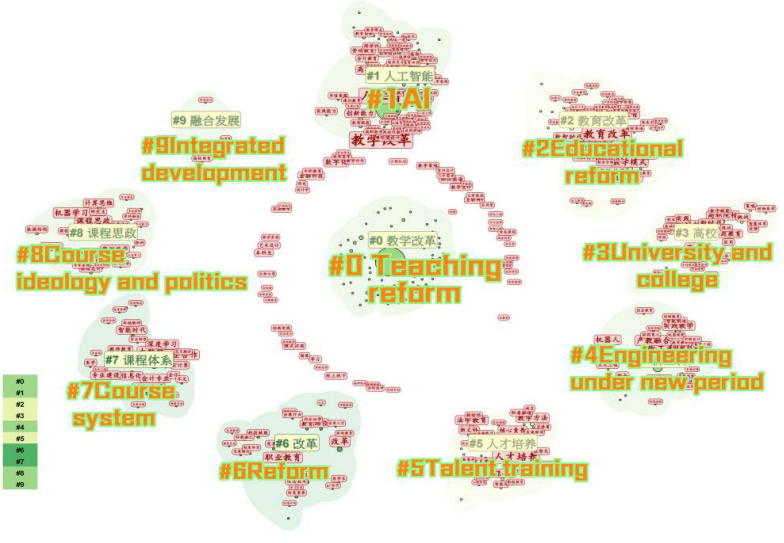


Figure 1. Keyword clusters for "AI" and "vocational" in CNKI, 2021–2025

Internationally, the clusters around AI comprise higher education, AI ethics, recruitment, virtual reality, large language models, vocational training, and fundamental rights, with generative AI emerging as a high-popularity term from 2023 onwards. Two implications follow. Domestically, AI should be advanced through the infrastructure and data channels that already exist—statistics, informationization and deep learning—because these supply both the data and the scenarios that AI needs. Internationally, the concentration of applied work in medical and technical domains, and the rapid rise of generative AI, indicate where domestic provision currently lags.

One caveat must be recorded. The Scopus portion of the international AI search returned a set of burst terms—including cancer rehabilitation, clinical development and cell therapy—that have no connection to vocational education and almost certainly indicate that the query over-retrieved. These terms are excluded from the analysis and from the indicator mapping; only the generative AI burst, which is substantively relevant, is carried forward. The retrieval strategy should be narrowed in future work.

3.4. Practice and deficiencies at the case college

Sichuan College of Architectural Technology has pursued four lines of work. Curricular reform is rebuilding the course system around data analysis under the Emerging Engineering Education initiative: course standards are being revised, and the compulsory/elective mix reconfigured so that student profiling and AI-driven recommendation can reshape individual pathways; the roadmap has been approved at leadership level. Faculty development rests on "dual-qualified" teachers supported by part-time industry instructors hired under tripartite agreements, with a national-level training base and an annually refreshed roster; in the Department of Engineering Management, more than 80% of 103 full-time teachers hold dual-competency certification, and 47 part-time instructors are engaged, 75% of them from state-owned enterprises. School-enterprise collaboration has produced off-campus internship bases with partners including Chengdu RuiLong Machinery Manufacturing and China Railway Engineering Services, a China-Australia virtual simulation base for prefabricated buildings, and, within the Digital Engineering Management Industry College, integration of AI and large language models into BIM instruction with AI-generated examination questions and AI-conducted assessment.

The survey, however, shows that provision and uptake are not the same thing, and four deficiencies recur. First, adoption of AI products and services remains incomplete: 16.7% of respondents have never used an AI educational tool, comprising 14.3% of teachers and 19.1% of students. Second, integration into curriculum development is still exploratory, and no systematic model exists; 80% of respondents believe AI could weaken learners' capacity for independent thought and 14.3% oppose introducing AI into discipline-specific courses, while preferences for implementation are split between embedding AI in compulsory core modules (31.4%) and offering stand-alone public electives (38.6%). Third, acceptance and skills training are weak: a substantial minority of both teachers and students hold neutral or negative attitudes, and the absence of systematic training produces uneven competence. Fourth, AI is barely present in practice bases—site teams still work to legacy processes, so generative-AI tools that dominate the bibliometric frontier are almost entirely absent from school-enterprise training.

4. The AI-Vocational Education Index

4.1. Indicator System

The AI-VEI is organized into four first-level dimensions covering the input-process-output chain, with twelve second-level indicators. Each indicator satisfies four conditions: it spans the full teaching chain; it is quantifiable from either objective platform data or a validated Likert-type item; it maps onto a CiteSpace hotspot or an explicit policy priority; and it foregrounds something specific to vocational education, such as practicum hours, certification rates, or co-teaching slots. **Table 1** gives the full matrix.

Table 1. The AI-VEI indicator system

First-level	Second-level indicator	Measurement	Basis	Data source
A. Curriculum & teaching	A1.1 Compulsory AI course share	AI class hours/total program hours	38.6% of respondents favor compulsory courses	Academic administration
A. Curriculum & teaching	A1.2 AI penetration of practical training	AI-containing projects/total projects	Vocational specificity; practice-based integration	Practical training outline
A. Curriculum & teaching	A1.3 AI share of digital resources	AI-enabled resources/ digital resources	"Informationization" and "deep learning" hotspots	Teaching platform
B. Faculty & team	B1.1 Teacher AI training participation	Trained teachers/program teachers	Modern meaning of "dual-qualified" teachers	Personnel office/ survey
B. Faculty & team	B1.2 AI skill rate of enterprise mentors	Mentors mastering AI skills/all mentors	Depth of industry-education integration	Interview/survey
B. Faculty & team	B1.3 AI teaching innovation cases	Count of AI-based teaching innovations per term	"Teaching method" in the three-teach reform	Teaching report/ evaluation
C. Student outcomes	C1.1 1+X certificate AI pass rate	Students passing AI-related 1+X exams/all students	"1+X certificate system", second-ranked CNKI keyword	Skills and qualifications center
C. Student outcomes	C1.2 Student AI project completion	Mean rubric score of comprehensive AI projects	Advanced capability and practical output	Work review/ platform data
C. Student outcomes	C1.3 AI tool usage activity	Mean weekly active hours on the AI training platform	Process data; objective usage habits	Platform log
D. Platform & environment	D1.1 Completeness of AI platform functions	Function coverage scored against industry standards	Material basis of "high-quality development"	Expert assessment
D. Platform & environment	D1.2 Joint school-enterprise AI projects	Count of joint AI development or application projects	Depth of industry-education integration	Research cooperation records
D. Platform & environment	D1.3 Generative AI tool access rate	Generative AI tools formally integrated into courses	International "generative AI" burst	Teaching plan

4.2. Weighting

Entropy weighting cannot be applied directly because the twelve indicators draw on incommensurable data sources. Instead, each indicator is anchored to the bibliometric statistic of the keyword it represents, and weights are built up in layers: a base layer from raw keyword frequency, a frontier layer that corrects for burst strength over the last three years, and a pivotal layer that applies a bounded adjustment for betweenness centrality. **Figure 2** shows the indicator-to-data mapping. Because CNKI keywords are counted and WOS keywords are scored by burst strength, the two scales are reconciled by treating one unit of WOS strength as equivalent to 100 units of CNKI count, after which all values are range-normalized over the interval [89, 1301]. Burst terms then receive a 1.5 multiplier and high-centrality terms a 1.2 multiplier before

normalization to a unit sum (**Table 2**).

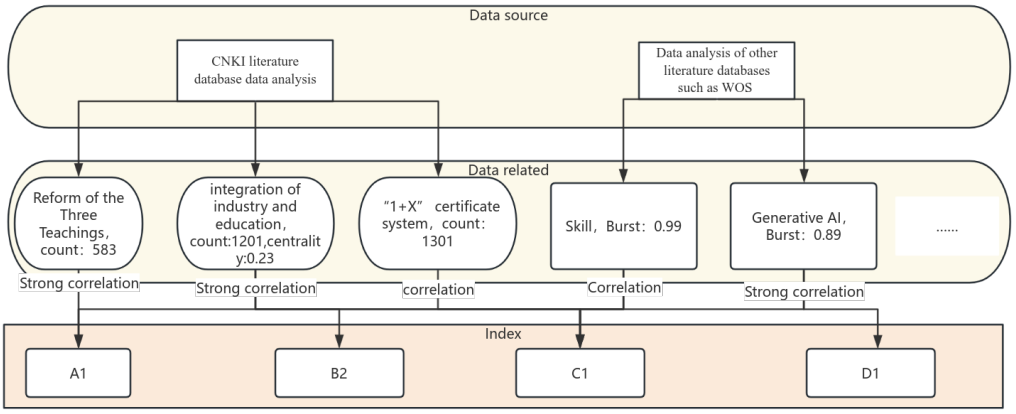


Figure 2. Mapping between AI-VEI indicators and their bibliometric data sources

Table 2. Objective (MCLF) weights, subjective (AHP) weights, and final weights

Indicator	MCLF weight %	AHP weight %	Final weight %
A1.1	0.16	2.22	5
A1.2	3.36	5.03	5
A1.3	3.34	6.02	5
B1.1	9.13	6.60	8
B1.2	24.67	2.54	12
B1.3	2.33	7.02	5
C1.1	22.39	10.88	13
C1.2	0.27	18.19	10
C1.3	3.00	19.52	12
D1.1	3.34	11.93	10
D1.2	24.67	5.86	10
D1.3	3.36	4.19	5
Total	100.00	100.00	100

The two columns diverge sharply and informatively. The objective column is dominated by B1.2 and D1.2 (24.67% each), because both are anchored to "integration of industry and education", which carries the third-highest keyword count (1,201) and the only recorded centrality value; C1.1 follows at 22.39% on the strength of the "1+X certificate system" (1,301). The subjective column reverses the ordering, placing C1.3 and C1.2—student tool usage and student project completion—first at 19.52% and 18.19%, because the expert panel, which included college leaders, argued that institutions should be judged on output and employability rather than on inputs. The AHP judgment matrix has a largest eigenvalue of 13.612 for twelve indicators, giving a consistency index of 0.147 and a consistency ratio of 0.095 against a random index of 1.54; this passes the conventional 0.10 threshold, but only marginally, and the matrix should be revisited before the weights are used for high-stakes decisions.

The final column is not a mechanical average of the two preceding columns. Pure averaging would leave C1.2 at 0.27% in the objective column, where a student who completed no AI project would be almost

unaffected, and would leave several indicators below the level at which they can influence a score at all. The published weights are therefore expert-adjusted to whole percentages that preserve the ranking of both columns while keeping every indicator operational; they sum to 100 and are the values used in the worked example. This adjustment is a judgment, and it is reported as such rather than presented as a computational result.

4.3. A worked example

Each indicator is scored on a banded scale whose maximum equals its weight in percentage points, so the index total is simply the sum of the twelve indicator scores and the maximum attainable score is 100. Table 3 gives the results for the case college. The college scores well on platform completeness (8 of 10), the 1+X certificate pass rate (9 of 13), and training participation (6 of 8), but weakly on faculty innovation cases (2 of 5) and generative AI tool access (3 of 5). The total is 62 out of 100. On the four-band scale adopted here—below 60 D, 60–75 C, 75–90 B, above 90 A—this corresponds to grade C: AI activity is clearly present and already produces measurable outputs, but penetration is uneven and has not yet reached the core of the curriculum.

Table 3. Worked example: AI-VEI scores for the case college

Indicator	Banding rule	Score/max
A1.1 Compulsory AI course share	0-25% → 0; 25-50% → 1-3; 50-75% → 3-4; ≥75% → 5	4/5
A1.2 AI penetration of practical training	0-25% → 0; 25-50% → 1-3; 50-75% → 3-4; ≥75% → 5	4/5
A1.3 AI share of digital resources	0-25% → 0; 25-50% → 1-3; 50-75% → 3-4; ≥75% → 5	4/5
B1.1 Teacher AI training participation	0-25% → 0-2; 25-50% → 3-5; 50-75% → 6-7; ≥75% → 8	6/8
B1.2 AI skill rate of enterprise mentors	0-25% → 0-2; 25-50% → 3-5; 50-75% → 6-9; ≥75% → 10-12	5/12
B1.3 AI teaching innovation cases	0-25% → 0; 25-50% → 1-3; 50-75% → 3-4; ≥75% → 5	2/5
C1.1 1+X certificate AI pass rate	0-25% → 0-2; 25-50% → 3-5; 50-75% → 6-9; ≥75% → 10-13	9/13
C1.2 Student AI project completion	≤60% → 0-2; 60-75% → 3-5; 75-90% → 6-9; ≥90% → 10	6/10
C1.3 AI tool usage activity	≤0.5 h → 0-4; 0.5-1 h → 5-8; 1-2 h → 9-11; ≥2 h → 12	5/12
D1.1 Completeness of AI platform functions	0-25% → 0-2; 25-50% → 3-5; 50-75% → 6-9; ≥75% → 10	8/10
D1.2 Joint school-enterprise AI projects	0-1 → 0-2; 1-3 → 3-5; 3-5 → 6-9; ≥5 → 10	6/10
D1.3 Generative AI tool access rate	0-25% → 0; 25-50% → 1-2; 50-75% → 3-4; ≥75% → 5	3/5
Total	Grade bands: <60 D; 60-75 C; 75-90 B; >90 A	62/100 → C

5. Discussion

The domestic literature is unambiguous that industry-education integration and high-quality development are the governing priorities, and the objective weights reflect exactly that emphasis. The survey, however, shows low acceptance among teachers and students and a weak coupling between AI and the practice bases where vocational competence is formed. Three proximate causes explain the gap. Infrastructure is incomplete, and because no AI-based educational system has been specified, institutions do not know what to build, so adoption stays low. New technology imposes additional learning costs that fall hardest on vocational students with weaker learning habits and on instructors habituated to established methods; student misuse of AI reinforces faculty skepticism. And industry-education integration, though treated as the employment solution, is itself still being piloted, so AI-enabled practice bases remain rare.

The AI-VEI is designed to act on precisely this gap. By scoring tool usage activity, platform completeness, and the penetration of practical training, it makes infrastructure and usage visible in the same metric as policy compliance, so that an institution cannot report AI adoption on paper while its training bases remain untouched. Its innovation is the combination of levels: macro research signals from CiteSpace, meso institutional practice, and micro perceptions from the survey enter one instrument. That said, the instrument measures penetration, not learning gain; a college could raise its score by deploying tools that students use without improving. Linking index scores to employment and certification outcomes is the necessary next validation step, and predictive applications of this kind have been demonstrated in comparable educational settings [25–26].

6. Conclusions, limitations and policy implications

This study mapped what domestic and international research attend to in vocational education reform and in AI applications to it, documented where implementation currently falls short at a representative construction vocational college, and built a twelve-indicator index that converts AI penetration into a single auditable score. Applied to the case college, the index returns 62 out of 100, grade C. The result is consistent with the survey evidence: AI is present in platforms and assessment, but has not reached the core curriculum, the faculty development system, or the practice bases. The study offers education authorities a way to move AI policy from binary presence checks to graded measurement, and offers colleges a diagnostic that identifies which of the four dimensions is holding the score down.

Four limitations bound these conclusions. The index has been tested at a single institution; although the team also holds data from a second college, generalisability remains untested. The questionnaire is small (n = 42), and item-level denominators vary, so the percentages should be read as indicative of the case college rather than of the sector. The model is static and cross-sectional; without longitudinal data, its predictive claim cannot be validated. And the weighting involves two discretionary judgments—the equivalence of one WOS strength unit to 100 CNKI counts, and the final rounding of weights to whole percentages—which should be tested for sensitivity in subsequent work.

Three groups of actors follow from the analysis. Institutions should run regular AI training that addresses resistance directly, and should build modular courses combining compulsory and elective components so that AI enters the core program rather than sitting beside it; enterprise partnerships to build "AI + architecture" case libraries would supply material that generic courses cannot. Education authorities should incorporate graded measures of AI penetration into Double-High Plan evaluations and annual quality reports, and fund AI-ethics work on data privacy and academic integrity in parallel. Enterprises should bring generative AI applications—automated drawing review, intelligent cost estimation—into joint projects so that practice bases expose students to the tools the labor market is beginning to reward.

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