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# Rethinking World University Rankings in the Age of AI: Introducing an AI Readiness Indicator

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# AI 시대 세계대학평가의 재고: AI 준비도 지표의 도입

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**Abstract** Global university rankings assess research, reputation, educational conditions, and internationalization, but they do not independently measure how broadly substantive artificial intelligence (AI) learning is distributed among students across an institution. Recent research has begun evaluating AI and digital readiness at the student, program, and institutional levels, yet limited work has connected such readiness with global university ranking structures. This study develops a concise AI Readiness Indicator (AI-RI) through a design-oriented comparison of major global, regional, and subject-ranking methodologies and scholarship on AI literacy and convergence education. AI-RI consists of Subject-Level AI Competitiveness (30%), Graduate AI Learning Coverage (45%), and Non-Major AI Learning Diffusion (25%). Publications and citations are not calculated separately because they are already incorporated into the relevant subject rankings. Qualifying student learning must include substantive AI content, assessment, and a responsible-use component. IoT, sensing, robotics, edge computing, and cyber-physical systems remain significant convergence applications but are not required in every qualifying course. For integration, the baseline ranking score and AI-RI are converted to a shared 0–100 scale. A 1% pilot weight and a 2% formal weight are proposed, subject to evaluation of data completeness, classification reliability, redundancy, equity effects, and rank sensitivity. The indicator is intended to function as a limited and auditable signal of readiness rather than a comprehensive assessment of university quality. Research on AI literacy similarly emphasizes multidimensional assessment involving knowledge, application, evaluation, and ethics.

**Key Words :** World University Rankings, AI Readiness, AI Literacy, AI Assessment, AI Education, IoT Convergence, QS Rankings, THE Rankings

**요 약** 세계대학평가는 대학의 연구, 평판, 교육환경과 국제화를 비교하지만, 인공지능(AI) 역량이 대학 전체 학생에게 얼마나 확산되는지는 독립적으로 측정하지 않는다. 최근 연구는 학생·학위과정·대학 차원의 AI 또는 디지털 준비도를 측정하기 시작했지만, 이를 세계대학평가의 명시적 구성요소로 연결하는 연구는 아직 제한적이다. 본 연구는 주요 세계·지역·학문분야 대학평가와 AI 리터러시 및 융합교육 문헌을 비교하여 기존 순위에 소규모로 결합할 수 있는 AI 준비도 지표(AI-RI)를 제안한다. AI-RI는 학문분야 AI 경쟁력 30%, 전체 학사 졸업생의 AI 학습이수율 45%, 비AI 전공 졸업생의 AI 학습확산율 25%로 구성한다. 연구논문과 인용은 관련 학문분야 평가에 이미 포함되므로 별도 지표로 중복 산정하지 않는다. 학생 학습은 실질적 AI 내용, 평가, 책임 있는 사용 요소를 갖춘 이수기록으로 확인하며, IoT·센싱·로보틱스·엣지컴퓨팅은 중요한 융합 적용영역으로 인정하되 필수 조건으로 두지 않는다. 기존 순위점수와 AI-RI는 통합 단계에서 공통 0-100 척도로 표현하고, 시범단계 1%, 정식단계 2%의 가중치를 제안한다. 본 지표는 기술이 대학의 모든 목적을 대체한다는 주장이 아니라, 전문역량과 전교적 AI 교육확산을 함께 보여주는 제한적이고 감사 가능한 보완지표이다.

**주제어 :** 세계대학평가, AI 준비도; AI 리터러시, AI 평가, 인공지능 교육, IoT 융합, QS Rankings, THE Rankings

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## 1. Introduction

Global university rankings influence student choices, institutional strategies, and public policy, while their indicators can shape organizational behavior. At the same time, rankings reduce complex institutions to simplified measures and remain sensitive to decisions concerning indicator selection, weighting, aggregation, and normalization[1–4]. Any additional component should therefore be narrowly specified, transparent, and proportionate to the broader purposes of higher education.

Existing global and subject-ranking methodologies focus on reputation, research impact, teaching environments, employability, internationalization, and related dimensions. AI strength may be reflected indirectly through performance in computer science or AI-related subjects, but major ranking systems do not independently assess whether substantive AI learning reaches the broader graduating population[5–9]. This creates a gap between specialist technical visibility and institution-wide educational preparation.

AI literacy is increasingly understood as extending beyond the use of tools. Major frameworks and studies emphasize understanding AI concepts, applying and evaluating AI systems, creating with AI, and addressing ethical or responsible use across disciplinary settings[10–14]. In university evaluation, this implies that verified learning completion should be measured rather than simply counting the AI courses listed in a catalogue. Recent AI-literacy research likewise supports multidimensional assessment across knowledge, application, critical evaluation, and ethics.

Recent studies have begun to operationalize readiness at multiple levels. Hua and Sun investigate AI readiness among college students; Russo et al. evaluate GenAI readiness at the degree-program level; Wu and Li develop an evaluation indicator system for AI certificate programs; and Chounta et al. propose a data-informed framework for institutional digital readiness in higher education[15–18]. Collectively, these studies demonstrate that readiness can be assessed beyond research output. However, they remain primarily diagnostic or educational-assessment frameworks rather than proposals for incorporating AI readiness into global university ranking systems. This study addresses that gap by translating AI readiness into a limited and auditable ranking component.

AI also functions within convergent technological environments. IoT, sensors, edge computing, robotics, and cyber-physical systems connect intelligent computation with physical and networked settings, and these applications are increasingly relevant to higher education and AIoT research[19–24]. In this paper, however, IoT is treated as an important application domain rather than a compulsory condition of AI readiness. The proposed AI Readiness Indicator (AI-RI) therefore examines whether a university combines credible AI and data capabilities with broad, assessable, and responsible AI learning among its graduates.

This paper develops an implementable indicator rather than proposing another comprehensive ranking system. It addresses three practical questions: what AI-readiness gap remains in current rankings, how can specialist strength and educational diffusion be measured without duplicating research indicators, and what data and validation rules are necessary for a small ranking component?

## 2. Background and Design Rationale

### 2.1 Ranking Gap

Rankings are selective and performative instruments: they make institutions comparable, but they can also redirect institutional attention toward the activities that receive recognition[1,2]. Technical critiques further demonstrate that rank positions may change under plausible modelling decisions, reinforcing the need for a bounded construct, explicit weighting, and robustness testing[3,4].

The central gap is not a lack of AI-related research measures. QS, THE, and ShanghaiRanking already incorporate research, reputation, and subject-level performance within their existing systems[5–9]. What remains largely unobserved is educational reach: whether students across an institution complete substantive AI learning and whether such learning extends beyond fields in which AI exposure is normally expected. Recent empirical studies have also identified regional disparities and methodological issues in the QS International Research Network indicator and THE's citation-based Research Quality measure[25,26].

## 2.2 AI Learning and Convergence

In this study, AI readiness refers to demonstrated institutional capacity to support both specialist strength in AI and data and verified student learning. Qualifying learning must include substantive AI concepts or methods, an assessable learning activity, and responsible-use content; ordinary digital literacy or unassessed use of generative AI does not meet this standard[10–14].

IoT and related connected-system fields remain particularly important because they demonstrate how AI operates through sensors, networks, embedded devices, and edge or cyber-physical environments[19–24]. They are therefore explicitly recognized as convergence contexts within qualifying courses and examples, while the core indicator remains applicable to business, design, science, public policy, humanities, and other fields.

## 2.3 Design Approach

The study adopts a design-oriented comparative approach rather than a systematic review or an empirical ranking exercise. QS, THE, and ShanghaiRanking were selected because they are widely recognized international ranking systems with publicly available methodologies, established global and subject-level frameworks, and differing indicator structures. Literature on AI literacy and readiness was selected based on its relevance to higher education, conceptual or operational treatment of AI literacy/readiness, and usefulness for defining measurable learning and institutional-readiness criteria. The literature was used to inform indicator design rather than to provide exhaustive systematic coverage. The study combines these official ranking methodologies with research on ranking measurement, AI literacy, and convergence education to develop a supplementary indicator that can be piloted using existing subject-ranking evidence and a limited set of auditable university submissions.

Four design principles guide the proposal: minimize duplication of existing research metrics; measure student-level completion rather than course availability; standardize denominators, field mappings, and eligibility criteria; and maintain a low overall weighting within the ranking. AI readiness is therefore narrower than institutional digital transformation but broader than department-level strength in AI research.

〈Table 1〉 Proposed dimensions and weights of AI-RI

| Dimension | Measurement | AI-RI weight | Overall ranking contribution |
|---|---|---|---|
| Subject-Level AI Competitiveness (S) | AI/data subject evidence on a common 0–100 scale | 30% | 0.6% |
| Graduate AI Learning Coverage (L) | Share of first-degree graduates completing a qualifying AI course, credential, or approved pathway | 45% | 0.9% |
| Non-Major AI Learning Diffusion (D) | Share of first-degree graduates outside designated AI majors completing qualifying AI learning | 25% | 0.5% |
| Total AI-RI | | 100% | 2.0% |

# 3. Proposed AI Readiness Indicator

## 3.1 Overview and Weights

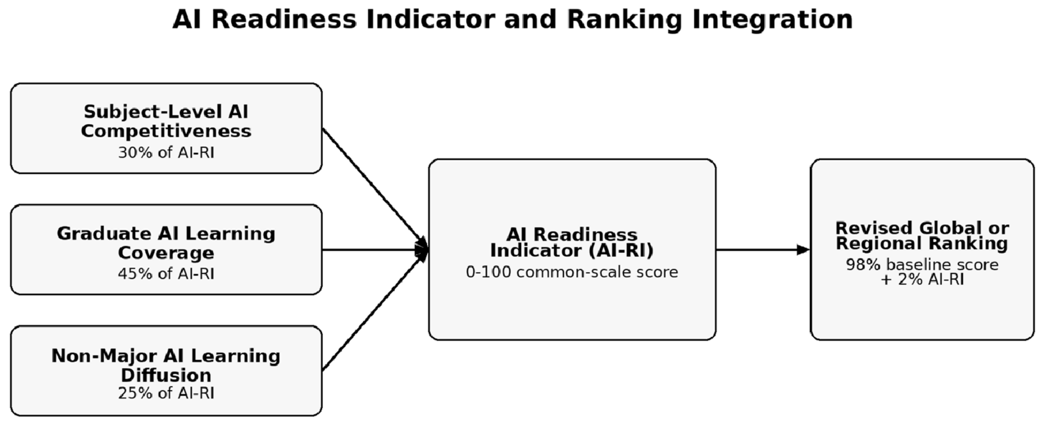
AI-RI is a composite score ranging from 0 to 100 and consisting of three dimensions. Subject-Level AI Competitiveness (S) accounts for 30%, Graduate AI Learning Coverage (L) for 45%, and Non-Major AI Learning Diffusion (D) for 25%. These values should be understood as provisional design weights rather than empirically optimized or formally validated coefficients. The initial allocation was informed by prior professional experience in university ranking methodology and ranking-system design, together with the conceptual objective of balancing specialist AI capability with institution-wide educational diffusion. S is assigned 30% to retain a meaningful signal of specialist AI capability while limiting duplication with research, reputation, and subject-level performance already embedded in existing ranking systems. L receives the largest weight (45%) because verified AI learning across the overall graduating population represents the primary educational-readiness construct of AI-RI. D receives 25% to capture additional cross-disciplinary diffusion while avoiding excessive double weighting, since non-major completers are already included within L. Thus, the combined 70% weighting assigned to L and D intentionally gives priority to educational diffusion rather than replicating an existing research ranking. The final calibration of these weights should be determined through empirical pilot testing. 〈Table 1〉 shows the three AI-RI dimensions, their measurement basis, and their respective weights within AI-RI and the overall ranking.

[Fig. 1] shows how the three components feed into a 0-100 AI-RI composite score and how the indicator is then integrated with the baseline global or regional ranking.

## 3.2 Subject-Level AI Competitiveness

S measures internationally visible capability in AI and data by using the highest approved AI/data subject score available from the ranking provider. Eligible fields may include Data Science and Artificial Intelligence, Computer Science and Information Systems, or clearly corresponding fields. Related engineering, IoT, or automation subjects may offer contextual information but cannot replace direct evidence of AI/data capability.

Let $A_i$ represent institution i's highest available AI/data subject score after conversion, where necessary, to a common 0-100 scale:




[Fig. 1] Structure of the proposed AI Readiness Indicator and its integration into rankings

$$S_i = A_i \tag{1}$$

Providers should disclose the eligible subject family and the transformation method. Published 0–100 scores may be used directly when compatible, whereas other scores or rank bands should be transparently rescaled. An institution's absence from a public subject table should not automatically be coded as zero when internal or approved external evidence is unavailable. No separate publication or citation component is included because these outputs are already reflected in subject rankings[7–9].

## 3.3 Graduate AI Learning Coverage

L measures the proportion of first-degree graduates who completed at least one qualifying AI learning experience during their degree. Completion must be documented at the student level, and multiple qualifying experiences completed by the same graduate are counted only once.

$$L_i = 100 \times (G_i / T_i) \tag{2}$$

$G_i$ denotes the number of unduplicated first-degree graduates completing qualifying AI learning in the reporting year, and $T_i$ is the total number of first-degree graduates in the same population. Postgraduate activity may be reported separately but is not included in the initial denominator.

## 3.4 Non-Major AI Learning Diffusion

D measures whether AI learning extends beyond predefined AI-related majors. It is the percentage of first-degree graduates outside the AI-major group who completed qualifying AI learning.

$$D_i = 100 \times (N_i / M_i) \tag{3}$$

$M_i$ is the number of first-degree graduates outside the standardized AI-major list, and $N_i$ is the number of those graduates completing qualifying AI learning. Major classification should use a disclosed international field-of-education crosswalk, such as ISCED-F 2013, with a provider-specific mapping for emerging AI programs[27].

D is nested within L because non-major completers are also included in the total graduating population. This arrangement is intentional. L measures the overall breadth of AI learning across all graduates, whereas D distinguishes whether that learning extends beyond AI-related majors. Separating the two helps prevent institutions with large specialist programs from appearing broadly AI-ready solely because many of their AI-related majors receive AI training. Thus, L captures overall coverage and D captures cross-disciplinary diffusion. Their correlation should nevertheless be tested during the pilot.

The objective is not to transform every graduate into an AI specialist. Qualifying learning can be discipline-specific—for example, AI-supported decision making in business, generative design, machine learning on sensor data, or algorithmic accountability in connected public services. Recent work has also demonstrated the feasibility of developing AI educational content specifically for non-IT-major university students, supporting the broader diffusion of AI learning beyond specialist disciplines[28].

## 3.5 Composite Formula and Ranking Integration

$$AI\text{-}RI_i = 0.30S_i + 0.45L_i + 0.25D_i \tag{4}$$

All three components are represented on a common 0–100 scale. L and D are institutional percentages, while S is converted according to the procedure described above. The common-scale requirement is an integration rule and does not mean that QS, THE, ShanghaiRanking, or other providers employ identical internal scoring or standardization methods.

Before integration, the baseline ranking score and AI-RI must both be expressed on a common 0-100 scale. The revised score is calculated as follows:

$$\text{Revised Score}_i(w) = (1 - w)B_i + w(\text{AI-RI}_i) \quad (5)$$

$B_i$ is the baseline ranking score on the common 0-100 scale and w is the AI-readiness weight. The recommended formal value is w = 0.02, preceded by a 1% pilot. Two percent is a proportional policy-design choice, not an empirically optimized parameter; formal use should depend on validation of data quality, redundancy, equity effects, and rank sensitivity.

## 4. Data, Eligibility, and Validation

### 4.1 Minimum University Submission

Each institution submits four unduplicated first-degree graduate counts: total graduates (T), graduates completing qualifying AI learning (G), non-AI-major graduates (M), and qualifying non-major graduates (N). A supporting file identifies the courses or pathways used to produce G and N. The ranking provider supplies the AI/data subject evidence for S, so universities need not report publication counts, GPU inventories, AI budgets, or numbers of devices deployed on campus.

### 4.2 Qualifying AI Learning

A qualifying learning experience may take the form of a credit-bearing course, an approved credential, or a formally connected pathway. It must include substantive AI content, assessed application or analysis, a responsible-use component, and auditable evidence of completion. IoT, sensing, robotics, edge computing, and cyber-physical applications are explicitly recognized as eligible convergence contexts but are not compulsory. 〈Table 2〉 shows the minimum criteria used to determine whether a learning experience qualifies for inclusion in AI-RI. Related research further suggests that sustainable AI practical education requires institutional support for scalable resource management, reliable access, and secure use of generative AI services[29].

### 4.3 Comparability, Audit, and Pilot Validation

Achieving international comparability requires transparent rules rather than assumed equivalence. Learning volume should be reported as documented learner activity alongside locally recognized credits, while AI-major classification should rely on a stable field crosswalk such as ISCED-F

〈Table 2〉 Minimum criteria for a qualifying AI learning experience

| Criterion | Minimum requirement |
|---|---|
| Formal status | Credit-bearing course, officially approved credential, or formally approved linked pathway recorded in the student information system |
| Minimum learning volume | At least 30 hours of documented learner activity in total; local credit values are reported separately rather than assumed to be internationally equivalent |
| Substantive AI content | Learning outcomes and assessment must explicitly address AI concepts, methods, application, evaluation, or creation; AI-related content accounts for at least 50% of the learning experience. IoT, sensing, edge computing, robotics, and cyber-physical systems may be used as applied convergence contexts but are not mandatory. |
| Assessment | Graded examination, project, portfolio, laboratory, or equivalent evaluation demonstrating application or analysis, not attendance alone |
| Responsible use | At least one assessed element addresses ethics, privacy, security, bias, accountability, safety, or appropriate human oversight in AI use or AI-enabled systems |
| Completion evidence | Student-level completion is auditable, unduplicated, and linked to the graduation year |
| Exclusions | One-off seminars, orientation sessions, unassessed tool demonstrations, and ordinary courses that merely permit AI use without substantive AI learning outcomes and assessment |

2013[27]. Interdisciplinary programs should be categorized according to documented curriculum content rather than their titles alone.

Audit requirements should include course codes, learning outcomes, assessment formats, completion totals, and syllabus documentation, together with checks for duplicate students, inconsistent denominators, and the relabeling of low-rigor courses. Reporting S, L, and D as separate components would also make unusual score patterns easier to identify.

Formal implementation should be preceded by a multi-institution pilot. Minimum validation checks should address data completeness, the reliability of independent course classification, component distributions and correlations, overlap with the baseline ranking, subgroup effects by institutional mission and type, audit burden, and rank sensitivity at 0%, 1%, 2%, and 3%. The pilot should also test alternative internal weighting schemes for S, L, and D and compare their effects on component contributions, score distributions, correlations with baseline ranking measures, institutional subgroup effects, and overall rank stability. A provider should postpone adoption if the indicator proves highly redundant, difficult to audit, or systematically biased.

A phased approach is therefore preferable: voluntary data collection without ranking consequences, a 1% pilot, and formal integration at 2% only after methodological review. Regional ranking products may apply the same construct, using provider-specific rescaling of the baseline score without changing the meaning of AI readiness.

## 5. Discussion and Limitations

### 5.1 Contributions and Interpretation

The primary contribution is the transition from assessing readiness to incorporating it into ranking systems. Recent research evaluates AI readiness at the student or program level and digital readiness at the institutional level[15–18], whereas AI-RI converts the construct into a small, auditable component for existing global and regional rankings. It combines visible subject-level capability with verified educational reach while omitting separate publication and citation measures that would duplicate information already included in current ranking systems.

The second contribution concerns the emphasis on completion and diffusion. Course catalogues indicate what institutions offer, but not who actually acquires the relevant learning. L measures the breadth of AI exposure among graduates, while D differentiates universities that extend AI learning beyond specialist majors. Together, these components make educational reach the dominant element of the index.

The model also preserves a clear convergence orientation without treating IoT as a universal requirement. IoT, sensing, robotics, edge computing, and AIoT remain important examples of AI operating in physical and networked environments[19–24]. However, AI learning in other disciplinary settings may also qualify when it satisfies the same standards of substantive content and responsible use.

Finally, the proposed 2% integration weight is deliberately limited. AI-RI should be understood as a signal of readiness rather than a comprehensive assessment of university quality. A high score does not indicate superiority in the humanities, basic sciences, creativity, civic education, student well-being, or other university missions.

### 5.2 Risks and Equity

Every ranking indicator can generate strategic responses. Universities might relabel existing courses, reduce assessment rigor, enroll large numbers of students in minimal modules, or manipulate denominators. These risks justify student-level records, shared eligibility rules, provider-controlled field mappings, and risk-based audits rather than reliance on a self-reported survey score[1].

Technology-related indicators may also advantage wealthy and research-intensive institutions. The design addresses this risk by assigning 70% of AI-RI to learning ratios rather than absolute resource levels, permitting low-cost or discipline-specific forms of AI learning, avoiding the automatic assignment of zero when subject rankings are unpublished, and limiting the indicator's total contribution to the ranking to 2%. Nevertheless, effects related to institutional mission and equity require explicit analysis during the pilot.

### 5.3 Limitations and Future Research

The proposal has not yet been validated using observed university data and should therefore be regarded as a testable indicator framework rather than a fully validated ranking indicator. The proposed 30:45:25 composition represents provisional design weights rather than empirically optimized or formally validated coefficients, and the 2% ranking weight is likewise a policy-design choice requiring empirical testing. Subject scores may still overlap with existing reputation and research indicators, while completion records function only as proxies for actual competence. Future multi-institution pilots should therefore compare alternative internal weighting schemes and eligibility thresholds through sensitivity analysis, examine component distributions and correlations, assess subgroup effects and auditability, and test rank stability before formal adoption. Where feasible, future studies may also incorporate sampled assessments or moderated credentials to complement completion-based measures.

Cross-national comparability will remain imperfect because credit systems, program structures, and ranking coverage vary across countries. AI itself will continue to develop through generative, embodied, edge, and connected forms. Periodic revision of field mappings and course criteria will therefore be necessary, although changes should be announced in advance to prevent unstable incentives.

## 6. Conclusion

This paper proposes a concise AI Readiness Indicator for limited incorporation into global and regional university rankings. AI-RI combines Subject-Level AI Competitiveness (30%), Graduate AI Learning Coverage (45%), and Non-Major AI Learning Diffusion (25%). Where possible, it relies on existing subject-level evidence, requires only four primary counts of first-degree graduates, and treats IoT and related connected environments as significant convergence applications rather than compulsory content.

The proposed model retains 98% of the baseline ranking score and assigns 2% to AI-RI after both measures have been converted to a common 0–100 scale, with a 1% pilot preceding formal implementation. Its purpose is not to redefine university excellence in technological terms, but to reveal whether credible AI capability is translated into broad, substantive, and responsible student learning. Empirical piloting should establish whether the proposed indicator is sufficiently reliable, distinctive, equitable, and auditable for formal adoption.

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