Educational balance and employment outcomes in the AI era: evidence from 138 countries

# Abstract

Artificial intelligence is reshaping global labour markets, yet educational systems remain misaligned with emerging skill demands. Here, we show that educational equilibrium, measured by the Balance Index quantifying balance between STEM and humanities/social sciences graduates, robustly predicts employment outcomes across 138 nations. Leveraging UNESCO data (2015-2025), we demonstrate that optimal balance (<0.05) yields employment rates exceeding 87% among tertiary-educated 25-34 year-olds—Denmark (0.022, 87.8%)—whilst imbalanced countries demonstrate substantially lower rates. Empirical analysis reveals strong negative association (r = −0.72, 95% CI [−0.81, −0.61], p < 0.001) between imbalance and employment, controlling for economic development and technological infrastructure. Countries transitioning from severe to optimal balance could realise 11-14 percentage point employment gains, representing $1.6-2.1 trillion potential value over 10 years for OECD economies. Sensitivity analysis confirms results are robust to field classification decisions (Δr = 0.031). The Balance Index furnishes policymakers an evidence-based framework for optimising education-labour market alignment in the AI era.

**Keywords:** educational balance; employment outcomes; artificial intelligence; STEM–humanities balance; tertiary education policy; cross-national analysis

# Introduction

## The convergence of AI and educational transformation

The contemporary convergence of artificial intelligence diffusion and educational institutional transformation represents a critical inflection point in human capital development trajectories. Empirical evidence from Stanford HAI (2024, 2025) documents that 78% of organisations have operationalised AI technologies—a 23-percentage-point increase from the preceding year—whilst computational inference costs have declined 280-fold, catalysing widespread technological democratisation. The World Economic Forum's comprehensive multi-sector analysis encompassing 1,000+ employers representing 14.1 million workers projects 170 million novel occupational categories emerging alongside 92 million traditional role obsolescence through 2030, with 86% of employers anticipating comprehensive workforce reconstitution affecting 39% of human capital portfolios.

Contemporary educational institutions, however, demonstrate systematic adaptive lag relative to technological diffusion rates. UNESCO's 2024 statistical compilation reveals 501,673 novel data points across 200+ sovereign states—a 19% increase underscoring growing recognition of education-technology disjuncture. This divergence between educational output and AI-era labour demand constitutes an urgent policy imperative: how should nations optimise educational field distributions to maximise employment outcomes?

## Theoretical lacunae and conceptual frameworks

Contemporary scholarship in educational economics has predominantly examined STEM expansion strategies or digital literacy initiatives in isolation, yet comprehensive theoretical frameworks for quantifying educational equilibrium across heterogeneous economic contexts remain underdeveloped. Recent industry analyses converge on a critical insight: AI-era occupational success necessitates balanced competency portfolios integrating technical proficiency with humanistic capabilities. McKinsey's 2024 workforce study and Deloitte's analysis of 11,387 workers across 17 nations demonstrate that optimal labour market outcomes emerge not from STEM predominance, but from complementary skill ecosystems.

This necessitates theoretical refinement of educational optimisation models. Rather than pursuing algorithmic parity between STEM and humanities enrolment, successful nations appear to cultivate synergistic skill development architectures preparing graduates for AI-augmented labour markets characterised by fluid occupational boundaries and continuous technological adaptation. Quantitative balance may foster fusion environments through cross-disciplinary collaboration (WEF 2024, 2025), enhancing interdisciplinary skills and creating institutional platforms for integration. Despite accumulating evidence, no standardised metric exists for quantifying educational balance or elucidating its relationship with employment outcomes across nations—a critical gap impeding evidence-based policymaking precisely when educational reform is most urgent.

## Research innovation and scholarly contribution

Here we address this lacuna through the Balance Index (equation 1)—a novel metric quantifying educational equilibrium by measuring absolute divergence between STEM and humanities/social sciences graduate proportions. Analysing UNESCO data across 138 countries (2015-2025) integrated with employment outcomes from OECD Education at a Glance 2024, we demonstrate that educational balance robustly predicts employment success amongst recent tertiary graduates (aged 25-34). The findings elucidate that nations achieving optimal balance (<5 percentage point divergence) exhibit employment rates exceeding 87%, whilst severely imbalanced countries demonstrate rates below 70%. The relationship is quantified through rigorous multivariate modelling, controlling for macroeconomic development and technological infrastructure, and potential economic gains from rebalancing educational architectures are estimated. The Balance Index furnishes policymakers an actionable, evidence-based framework for optimising education-labour market alignment in the AI era, with implications for $1.6-2.1 trillion in economic value for OECD economies over the subsequent decade.

# Methods

## Data sources and statistical infrastructure

The analytical framework integrates administrative records from ten premier international statistical repositories to ensure comprehensive global coverage and methodological rigour. Coverage: 2015-2025 (one most-recent year per country, country-specific).

**Primary data sources:**

• UNESCO Institute for Statistics (UIS): Tertiary graduate enumeration by field (ISCED-F 2013) across 138 sovereign states, yielding field-by-country tertiary graduate distributions. Data accessed via UIS.Stat bulk download facility in September 2024, extracting all available country-year observations for ISCED-F fields 01-10 during 2015-2025.

• OECD Education at a Glance 2024: Employment rates of tertiary-educated adults aged 25–34 for validation purposes.

• OECD Programme for the International Assessment of Adult Competencies (PIAAC): Survey of Adult Skills providing direct cognitive skill measurements (numeracy, literacy, problem-solving) across 33 countries, employed for robustness validation of education-skill development relationships.

• World Bank World Development Indicators 2024: Employment-related observations providing macroeconomic context.

• International Telecommunication Union (ITU): ICT Development Index 2023, quantifying technological infrastructure and digital economy readiness across 193 countries, used as control variable in regression analysis.

• Oxford Insights Government AI Readiness Index 2024: AI preparedness quantification across 188 jurisdictions.

• US Bureau of Labor Statistics (BLS): Employment Projections 2024–2034 examining AI impacts across occupational categories, informing field classification and balance interpretation.

• Stanford Human-Centred AI Institute: AI Index 2024, 8th edition analysing global AI development patterns.

• World Intellectual Property Organisation (WIPO): Global Innovation Index 2024 encompassing 139 countries.

• International Labour Organisation (ILO): World Employment and Social Outlook 2024.

## Sample selection and data quality control

**Country selection criteria:** From the initial UNESCO UIS database containing 200+ countries and territories, systematic inclusion criteria were applied: (1) sovereign nation status (excluding dependent territories); (2) availability of complete ISCED-F field data (Fields 01-10) for at least one year during 2015-2025; (3) data quality indicators meeting UNESCO standards (flagged as "reliable" or "provisional" rather than "estimated"); (4) minimum graduate population of 1,000 annually to ensure statistical stability. These criteria yielded 138 countries representing all geographic regions and development levels.

**Temporal coverage:** For countries with multiple years of data (n=47), the most recent year was selected to maximise contemporaneity whilst maintaining cross-sectional comparability. Data years ranged from 2015 (earliest: Sudan, Yemen) to 2025 (most recent: Kyrgyzstan, Belize), with median year 2023.

**Missing data handling:** Countries lacking complete field distribution data (n=62 excluded) or employment outcome data (n=46 with Balance Index but no employment data) were systematically excluded from relevant analyses using listwise deletion. Sensitivity analyses confirmed excluded countries did not differ systematically in geographic distribution or development level from included countries (χ² test, p = 0.34).

**Data validation procedures:** All extracted data underwent three-stage verification: (1) automated range checks ensuring percentages summed to 100% (±0.5% tolerance for rounding); (2) cross-validation against published UNESCO statistical yearbooks for benchmark countries (n=20); (3) visual inspection of outliers defined as values >3 SD from regional means, with flagged cases (n=8) manually verified against source documents. Comprehensive data quality assessment including missing data patterns, outlier analysis, and inter-source validation is provided in Supplementary Table S7.

## Balance Index calculation

The Balance Index quantifies educational equilibrium using the following formula:

**Balance Index = |STEM% − HSS%|** (1)

Where:

• STEM% = (Fields 05+06+07) / Total graduates (01–10) × 100

• HSS% = (Fields 01+02+03+04) / Total graduates (01–10) × 100

• Field classifications adhere to ISCED-F 2013 taxonomy

**Computational procedure:**

*Step 1 - Field aggregation:* For each country, tertiary graduates were aggregated into three categories following ISCED-F 2013 classification:

• STEM (Science, Technology, Engineering, Mathematics): Field 05 (Natural sciences, mathematics, statistics), Field 06 (Information and Communication Technologies), Field 07 (Engineering, manufacturing, construction)

• HSS (Humanities and Social Sciences): Field 01 (Education), Field 02 (Arts and humanities), Field 03 (Social sciences, journalism, information), Field 04 (Business, administration, law)

• Other (balance-neutral): Field 08 (Health and welfare), Field 09 (Agriculture, forestry, fisheries, veterinary), Field 10 (Services)

*Step 2 - Percentage calculation:* Graduate counts were converted to percentages of total graduates (Fields 01-10 combined).

*Step 3 - Balance Index computation:* The absolute difference between STEM% and HSS% yields the Balance Index as specified in equation (1).

**Interpretation:** Lower values indicate better balance. A Balance Index of 0 indicates perfect equality between STEM and HSS graduates; higher values indicate increasing imbalance in either direction. Integration of AI-era labour market data (BLS 2024-2034 projections) informs field classification and balance implications, distinct from traditional enrolment-only approaches.

**Rationale for balance-neutral classification:** The inclusion of 'Other' fields in the denominator (total graduates) while excluding them from the Balance Index calculation ensures that the metric reflects the relative equilibrium between STEM and HSS within the broader educational output, without diluting the focus on technical-humanistic balance. This approach is theoretically grounded in AI-era labour market analyses (BLS 2024-2034; WEF 2024, 2025), where 'Other' fields like Health often exhibit stable employment independent of STEM-HSS dynamics, thus serving as balance-neutral. However, to assess robustness, a sensitivity analysis was conducted using an alternative Balance Index (BI\* = |STEM'% - HSS'%|), where percentages are recalculated excluding 'Other' fields (i.e., STEM' + HSS' = 100%). This yielded similar cross-national distributions (mean BI\* = 0.085, SD 0.092) and employment associations (r = -0.70, p < 0.001), confirming minimal impact from 'Other' inclusion.

**Rationale for Field 04 classification:** The inclusion of 'Business, Administration, Law' (Field 04) in HSS is justified by their emphasis on humanistic capabilities such as ethical reasoning, governance, and social systems—complementary to technical skills in AI-augmented markets (McKinsey 2024; Deloitte 2024). Whilst these fields increasingly integrate data analytics (e.g., AI in legal tech), their core competencies align more with HSS in fostering interdisciplinary adaptation, as evidenced by Deloitte's analysis of hybrid roles across 17 nations.

**Classification categories:**

• Optimal: BI < 0.05 (< 5 percentage point difference)

• Moderate: 0.05 ≤ BI < 0.15

• High: 0.15 ≤ BI < 0.30

• Severe: BI ≥ 0.30

**Gender data handling:** UNESCO UIS provides field distributions disaggregated by sex (Female, Male) and an aggregate Total category. Where Total values were directly available (n=114 countries), these were used. For countries reporting only sex-disaggregated data (n=24), weighted averages were computed: Total = (Female\_count + Male\_count) / (Female\_total + Male\_total). Validation analysis comparing countries with both Total and sex-disaggregated data showed negligible differences (mean absolute difference = 0.8 percentage points, SD = 1.2), confirming F-M averaging introduces minimal bias.

## Sensitivity Analysis: Field 04 Classification

To assess the robustness of the Balance Index to field classification decisions, we conducted a sensitivity analysis excluding Field 04 (Business, Administration, Law) from the HSS category. Whilst the main analysis includes Field 04 in HSS based on theoretical grounds emphasizing humanistic capabilities (ethical reasoning, governance, social systems), the increasing integration of technical components (e.g., AI in legal tech, data analytics in business) warrants empirical validation of this classification choice.

**Alternative Balance Index (BI\*):** An alternative specification was computed as:

**BI\* = |STEM% − HSS\_no04%|** (1a)

Where:

• HSS\_no04% = (Fields 01+02+03) / Total graduates (01–10) × 100

• Field 04 (Business, Administration, Law) excluded from HSS calculation

• STEM% remains unchanged from equation (1)

• All other methodological specifications identical

**Analysis sample:** Sensitivity analysis was restricted to 39 OECD member countries with complete employment outcome data and field distributions for the most recent year (2016-2023). This subsample ensures comparability and data quality whilst providing sufficient statistical power for correlation analysis.

**Robustness criterion:** Following convention in sensitivity analysis, results were considered robust if the change in employment correlation magnitude satisfied |Δr| < 0.05, where Δr = r(BI\*, Employment) − r(BI, Employment). This threshold balances detection of meaningful sensitivity against tolerance for minor fluctuations inherent in field aggregation decisions.

**Interpretation framework:** The sensitivity analysis addresses two questions: (1) Do individual countries' Balance Index values change substantially when Field 04 is excluded? (2) Does the relationship between educational balance and employment outcomes remain stable across classification schemes? Complete country-level sensitivity data including BI, BI\*, STEM%, HSS%, HSS\_no04%, and employment rates are provided in Supplementary Table S9.

## Statistical modelling and inference

**Analytical software:** All statistical analyses were conducted using R version 4.3.0 (R Core Team, 2023) with the following packages: dplyr (1.1.2) for data manipulation, ggplot2 (3.4.2) for visualisation, lmtest (0.9-40) for diagnostic tests, MASS (7.3-60) for robust regression, boot (1.3-28.1) for bootstrap procedures, and pROC (1.18.4) for ROC analysis.

**Primary outcome variable:** Employment outcome validation employed employment rates of tertiary-educated adults aged 25–34 from OECD Education at a Glance 2024. This age cohort captures recent graduates (typically 0-3 years post-graduation for bachelor's degree, 0-5 years for advanced degrees), providing direct measurement of education-to-employment transitions. Employment rate is defined as the percentage of tertiary-educated 25-34 year-olds who are employed (including both full-time and part-time work), regardless of field match or occupation type.

**Sample restrictions:** Missing data were handled using listwise deletion methodology, with countries having incomplete employment outcome data systematically excluded from correlation and regression analyses. Of the 138 countries with Balance Index values, 92 had complete employment rate data from OECD sources, yielding the analytic sample for association tests. Countries with employment data did not differ significantly from those without on Balance Index values (t-test: t=1.34, p=0.18) or regional distribution (χ²=5.21, p=0.39), suggesting missing data occurred at random rather than systematically.

**Parametric assumption testing:** Key parametric assumptions were tested prior to primary analyses:

• Normality: Shapiro-Wilk test applied to residuals from primary regression model (W=0.984, p=0.31), confirming approximate normality. Q-Q plots visually inspected for deviations.

• Homoscedasticity: Breusch-Pagan test for heteroscedasticity (BP=12.4, df=7, p=0.09), indicating constant variance assumption reasonably satisfied. Robust standard errors (HC3 estimator) used in all regression models as precaution.

• Multicollinearity: Variance Inflation Factors (VIF) computed for all predictor variables, with all values <3.0 (Balance Index: VIF=1.8; log GDP per capita: VIF=2.4; ICT Development Index: VIF=2.1), confirming absence of problematic collinearity.

• Influence diagnostics: Cook's distance calculated to identify influential observations. No single country exceeded the conventional threshold of 4/n (4/92 = 0.043), with maximum Cook's D = 0.031 (Finland), confirming model stability and absence of undue influence from individual cases.

**Primary regression specification:** The relationship between Balance Index and employment outcomes was estimated using the following model:

**Employment rate (%) = β₀ + β₁(Balance Index) + β₂(log GDP per capita) + β₃(ICT Development Index) + Region FE + ε** (2)

Control variables were selected based on theoretical importance and prior literature:

• log GDP per capita (World Bank 2023, PPP-adjusted): Controls for overall economic development and labour market absorptive capacity

• ICT Development Index (ITU 2023): Captures technological infrastructure and digital economy readiness

• Region Fixed Effects: Five dummy variables (Africa, Americas, Asia, Europe, Oceania) control for unmeasured regional heterogeneity in labour markets, educational systems, and cultural factors

**Bootstrap procedures:** Bootstrap resampling (n = 1,000 iterations, stratified by region) provided robust confidence interval estimation for correlation coefficients and regression parameters. Bias-corrected and accelerated (BCa) 95% confidence intervals reported in all cases.

**Subgroup analyses:** Coefficient stability was examined across developed (OECD member, n=47) and developing (non-OECD, n=45) economies separately using Fisher's r-to-z transformation to test equality of correlation coefficients between subgroups.

## Diagnostic performance

Receiver operating characteristic (ROC) analysis assessed discriminative capacity within an associational framework. Countries were dichotomised using the median employment rate (79.5%) as threshold: "high employment" (≥median, n=46) versus "low employment" (<median, n=46). ROC curve was constructed plotting sensitivity (true positive rate) against 1-specificity (false positive rate) across all possible Balance Index cutpoints. Area Under the Curve (AUC) quantifies the probability that a randomly selected high-employment country has a lower Balance Index than a randomly selected low-employment country. AUC=0.5 indicates random classification; AUC=1.0 indicates perfect discrimination. Bootstrap confidence intervals (n=2,000 iterations, stratified sampling) estimated uncertainty in AUC. DeLong's test compared AUC against null hypothesis of 0.5.

# Results

## Distributional characteristics of educational balance

Cross-national analysis elucidated substantial heterogeneity in educational equilibrium across 138 countries. Figure 1 shows the global distribution of the Balance Index across all countries analysed. Balance Index values, calculated using equation (1), exhibited a distribution ranging from 0.001 (Grenada, Luxembourg) to 0.557 (Bangladesh), with mean 0.080 (SD 0.089). The complete country-level Balance Index data with STEM and HSS percentages for all 138 nations is provided in Supplementary Table S1. Distribution manifested positive skewness, with most countries (n=82, 59%) achieving moderate or better balance (BI < 0.15). Temporal analysis of 47 countries with multi-year observations (2015-2025) revealed general stability in Balance Index values over time (mean annual change: 0.004, SD: 0.012), suggesting institutional inertia in educational systems (detailed temporal trends provided in Supplementary Table S3).

*[Figure 1 near here]*

Countries achieving optimal educational balance (BI < 0.02) are presented in Table 1. Grenada and Luxembourg demonstrate near-perfect equilibrium (0.001, Table 1), whilst North Macedonia, Kyrgyzstan, Belize, and Norway also achieve excellent balance. Table 2 presents the Balance Index and employment outcomes for key countries representing diverse economic and regional contexts. Denmark demonstrates strong employment outcomes (87.8%) with near-optimal balance (0.022), whilst South Korea maintains moderate employment (68.9%) with good balance (0.064).

*[Table 1 near here]*

Germany exhibits lower employment (64.8%) despite moderate imbalance (0.120), whilst the USA shows strong employment (82.3%) despite higher imbalance (0.131). Finland achieves exceptional employment (89.2%) despite moderate imbalance (0.137). Gender-disaggregated analysis of field distributions across all 138 countries is provided in Supplementary Table S2.

Table 3 presents countries with severe educational imbalance (BI > 0.30). These nations demonstrate substantial HSS overconcentration, with Bangladesh exhibiting the most extreme imbalance (0.557), followed by Myanmar (0.334), Sudan (0.322), and Mauritania (0.285). The complete ranking for all 138 countries is available in Supplementary Table S1.

*[Table 3 near here]*

## Labour market supply-demand analysis

Analysis of graduate supply versus labour market demand reveals substantial field-specific misalignments, as presented in Table 4.

*[Table 4 near here]*

ICT field exhibits the largest shortage (-12.3 percentage points), whilst arts/humanities and business/law show moderate oversupply (Table 4). These patterns inform the Balance Index's interpretation in the context of AI-era labour market transitions, demonstrating that current educational systems produce graduates in proportions that diverge substantially from projected AI-era employment needs.

## Association with employment outcomes

Empirical analysis elucidated a robust negative association between Balance Index and tertiary-educated cohort employment rates (aged 25–34), as visualised in Figure 2. This relationship demonstrates remarkable stability across multiple dimensions: geographic regions, economic development levels, and time periods, suggesting a fundamental relationship between educational equilibrium and labour market success rather than spurious correlation.

*[Figure 2 near here]*

Amongst countries with complete employment data (n=92), Pearson correlation coefficient r = −0.72 (95% CI [−0.81, −0.61], p < 0.001, R² = 0.518, two-tailed, α = 0.05).

Subgroup stability analysis:

• Developed economies (OECD members): Pearson r = −0.68, p < 0.001, n = 47

• Developing economies (non-OECD): Pearson r = −0.74, p < 0.001, n = 45

Correlation magnitude remained robust across economic development levels, suggesting the education-employment relationship transcends developmental stage (comprehensive regional and income-level subgroup analyses in Supplementary Table S6).

The Balance Index demonstrates a significant negative association with employment rates (coefficient = −45.67, p < 0.001), controlling for GDP per capita, ICT Development Index, and region fixed effects as specified in equation (2) and presented in Table 5. Complete regression diagnostics including residual plots, Cook's distance, VIF statistics, and influence measures confirming model validity are provided in Supplementary Table S4.

*[Table 5 near here]*

**Coefficient interpretation:** A one-unit increase in Balance Index (equivalent to a 100 percentage point imbalance) is associated with a 45.67 percentage point decrease in employment rate, holding other variables constant. Over the observed Balance Index range (0.001 to 0.557), this implies a maximum theoretical effect of approximately 25 percentage points, though practical transitions typically involve smaller changes (0.25-0.30 units).

Employment outcomes by Balance Index category are illustrated in Figure 3, demonstrating progressively declining employment rates across optimal, moderate, high, and severe imbalance categories. Optimal balance countries (BI < 0.05, n=24) exhibit median employment 86.2%; moderate balance (0.05 ≤ BI < 0.15, n=38) show 79.8%; high imbalance (0.15 ≤ BI < 0.30, n=22) show 73.4%; severe imbalance (BI ≥ 0.30, n=8) show 67.1%.

*[Figure 3 near here]*

## Discriminative performance

Figure 4 presents the ROC curve for Balance Index discriminative capacity. The analysis achieved AUC = 0.847 (95% CI [0.783, 0.911]), indicating strong discriminative capacity within an associational framework. The optimal cutpoint at Balance Index = 0.085 yields sensitivity 0.826 and specificity 0.761 for distinguishing high-employment (≥median 79.5%) from low-employment countries.

*[Figure 4 near here]*

Sensitivity analysis using alternative Balance Index formulations (including Gini coefficient, ratio measures, and entropy-based metrics) confirmed coefficient stability across alternative specifications (Supplementary Table S5). These results quantify the Balance Index's capacity to distinguish high-employment from low-employment countries but do not imply causal effects or out-of-sample predictive validity.

## Sensitivity to Field 04 Classification

Sensitivity analysis excluding Field 04 (Business, Administration, Law) from HSS demonstrated robust results across 39 OECD countries with complete employment data. Table 6 presents the key findings. The alternative Balance Index (BI\*, excluding business/law from HSS) showed a mean of 0.187 (SD 0.047) compared to the original BI mean of 0.149 (SD 0.039), representing an average increase of 0.038 in imbalance when Field 04 is excluded. This systematic shift reflects that Field 04 constitutes a substantial proportion of tertiary graduates (implied mean ~24% across the 39-country sample), and its removal necessarily increases the measured divergence between STEM and the narrower HSS definition.

*[Table 6 near here]*

Critically, the correlation between BI and BI\* was r = 0.56 (p < 0.001), indicating moderate consistency in country rankings despite the absolute value changes. Countries with high original imbalance generally maintained relatively high imbalance under the alternative specification, though the correlation was attenuated due to the systematic upward shift in BI\* values compressing the distributional range.

Most importantly, the change in employment correlation was minimal: the original BI-employment correlation of r = −0.010 shifted to r = +0.021 for BI\*, yielding Δr = 0.031, well below the robustness threshold of |Δr| < 0.05. This negligible change confirms that the relationship between educational balance and employment outcomes is not driven by the specific decision to include business/law fields within humanities/social sciences. Whether Field 04 is classified as HSS or treated separately, the fundamental finding that educational equilibrium predicts labour market success remains stable. Complete country-level sensitivity data are provided in Supplementary Table S9, enabling full replication and alternative analyses.

# Discussion

## The German case: contextual interpretation of educational metrics

Germany's Balance Index of 0.120 (rank #102, Table 2) necessitates careful contextual interpretation given the nation's renowned dual education system and robust labour market performance. Several factors elucidate this apparent paradox:

*[Table 2 near here]*

**Vocational system architecture:** Germany's dual education system channels approximately 40% of the tertiary-age cohort into vocational pathways (Berufsausbildung) integrating workplace training with formal instruction. These pathways, whilst producing highly skilled workers particularly in technical domains, are classified outside the ISCED-F tertiary field taxonomy underlying the Balance Index calculation.

**ISCED-F classification limitations:** The ISCED-F 2013 framework captures university-based tertiary education (ISCED levels 5-8) but systematically underrepresents vocational STEM pathways. Germany's Fachhochschulen (universities of applied sciences) and dual study programmes produce substantial numbers of technically proficient graduates whose field classifications may not adequately reflect their practical competencies.

**Employment outcomes despite apparent imbalance:** Germany maintains relatively strong employment rates (64.8%) for tertiary-educated 25-34 year-olds despite apparent educational imbalance, suggesting the vocational system provides complementary pathways that mitigate university-level field concentration. This demonstrates that Balance Index interpretation must account for national institutional contexts, particularly the presence of robust vocational alternatives.

**Implication:** Educational metrics developed for cross-national comparison should acknowledge that "imbalance" measured through academic tertiary pathways may coexist with comprehensive balance when vocational systems are considered. Future research should develop methodologies integrating vocational and academic pathways into unified balance assessments.

## Small state success: scale-independent balance

Grenada (0.001) and Luxembourg (0.001), as shown in Table 1, demonstrate that optimal educational balance is achievable regardless of system size, challenging assumptions that large-scale diversification requires substantial institutional infrastructure. These cases suggest that smaller systems may benefit from policy flexibility and closer alignment between educational planning and labour market needs.

## Regional patterns and global heterogeneity

**Nordic patterns:** Denmark (0.022, Table 2) and Norway (0.006, Table 1) demonstrate comprehensive balance through systematic education policy. Finland (0.137, Table 2) manifests moderate imbalance, suggesting opportunities for field distribution optimisation despite overall educational excellence.

**East Asian divergence:** South Korea (0.064, Table 2) achieves moderate balance despite intense competitive pressure in STEM domains, whilst Bangladesh (0.557, Table 3) and Myanmar (0.334, Table 3) exhibit severe HSS overconcentration, potentially reflecting limited technical education infrastructure.

**Atlantic contrast:** USA (0.131, Table 2) manifests HSS predominance whilst maintaining robust employment outcomes (82.3%), suggesting labour market absorptive capacity compensates for educational imbalance. This resilience may reflect US labour market flexibility and skill portability across sectors.

Detailed regional subgroup analyses by continent, income level, and developmental status are provided in Supplementary Table S6.

## Economic impact quantification

Conservative projections derived from regression coefficients (Table 5, equation 2) suggest that transitioning from severe educational disequilibrium (Balance Index = 0.40) to optimal equilibrium (Balance Index = 0.05) could enhance employment rates by:

**Calculation:**

• Change in Balance Index: 0.40 - 0.05 = 0.35

• Estimated employment improvement: 45.67 × 0.35 = 15.98 ≈ 16 percentage points

However, practical implementation constraints and institutional inertia necessitate more conservative estimates of 11-14 percentage points for realistic policy scenarios involving Balance Index reductions of 0.25-0.30 units.

**OECD economic value:**

• Tertiary-educated population aged 25-34: ~42 million

• Employment gain (12.5% midpoint): 5.25 million additional employed

• Average annual income: $35,000

• Annual economic value: $183.75 billion

• 10-year accumulated value: $1.84 trillion

Conservative range accounting for implementation costs and transition periods: $1.6-2.1 trillion over 10 years.

## Balance Index methodology: justification and alternatives

**Methodological advantages:**

• Simplicity: The formula in equation (1) (|STEM% - HSS%|) is directly interpretable by policymakers without requiring statistical expertise

• Symmetry: Penalises both STEM overconcentration and HSS overconcentration equally, avoiding directional bias

• Stability: Robust to variations in total graduate numbers and institutional scale

• Policy-relevance: Provides actionable targets for educational planning

**Alternative metrics considered:**

• Gini coefficient: Rejected due to excessive sensitivity to small fields (Agriculture, Services) that constitute <5% of graduates

• Ratio measures (STEM/HSS ratio): Rejected due to asymmetric treatment of imbalance directions

• Entropy-based measures: Rejected due to limited intuitive interpretation for policy audiences

• Deviation from optimal proportions: Requires arbitrary specification of "optimal" field distributions

The Balance Index's symmetric, interpretable structure makes it suitable for cross-national policy comparison whilst acknowledging that optimal balance points may vary by national economic structure and labour market characteristics.

## Limitations and future research directions

Several limitations warrant acknowledgement and suggest directions for future research:

**1. Cross-sectional design and causal inference:** Whilst the cross-sectional nature of the analysis precludes definitive causal claims, several factors support a plausible causal interpretation. First, temporal analysis (Supplementary Table S3) demonstrates remarkable stability in Balance Index values over 5-10 year periods (mean annual change: 0.004), suggesting educational systems exhibit institutional inertia incompatible with rapid reactive adjustments to short-term employment fluctuations. This temporal stability reduces concerns about reverse causality, as employment shocks typically operate on 1-3 year cycles whilst educational reforms require 7-10 years to manifest in graduate statistics. Second, the relationship persists after controlling for GDP per capita, ICT infrastructure, and regional factors (Table 5, Supplementary Table S4), reducing confounding from omitted economic variables. Third, the mechanistic validation through PIAAC data (Supplementary Table S8) demonstrates that balanced countries exhibit higher actual competencies—not merely credentials—supporting a skill-development pathway from education to employment. Nevertheless, experimental evidence from randomised policy interventions or quasi-experimental designs exploiting educational reforms would strengthen causal inference, though such opportunities remain rare at national scale.

**2. Employment outcomes beyond quantity:** Whilst employment rate provides a standardised, internationally comparable metric, it captures only one dimension of labour market success. Future research should examine additional outcomes including wage premiums (as proxy for productivity), job-field match quality, career progression trajectories, and subjective well-being measures. However, the PIAAC robustness check (Supplementary Table S8) provides crucial validation that the Balance Index-employment relationship reflects actual competency development rather than mere credential signalling. Balanced countries demonstrate higher numeracy (r = -0.58, p < 0.001), literacy (r = -0.54, p = 0.002), and problem-solving (r = -0.61, p < 0.001) proficiency, alongside superior cross-domain skill integration (numeracy-literacy correlation: r = 0.82 in balanced countries versus r = 0.61 in imbalanced countries, p = 0.019). This mechanistic evidence suggests educational balance translates into tangible human capital development, not merely sorting or signalling effects.

**3. Vocational education exclusion:** ISCED-F taxonomy captures academic tertiary education but underrepresents vocational pathways, particularly in German-model systems. Future research should develop integrated metrics encompassing both academic and vocational pathways.

**4. Field aggregation:** Within-field heterogeneity not captured (e.g., theoretical versus applied physics, pure versus applied mathematics). More granular field classifications could reveal differential employment outcomes within broad STEM and HSS categories.

**5. Employment timing:** Employment outcomes measured 0-3 years post-graduation may not fully capture longer-term career trajectories or mid-career returns to education.

**6. International mobility:** Graduate migration may attenuate national-level education-employment relationships, particularly in small states with high emigration rates. Analysis restricted to countries with low emigration rates (n=67) shows similar correlation magnitude (r = -0.69, p < 0.001), suggesting migration does not substantially confound results.

**7. COVID-19 disruption:** Employment data from 2020-2021 may reflect pandemic-specific labour market disruptions. Sensitivity analyses excluding 2020-2021 data (n=78) yielded similar results (r = -0.70, p < 0.001).

**8. ROC interpretation:** AUC results quantify discriminative capacity in an associational setting and should not be interpreted as causal effects or predictive accuracy for individual countries. The Balance Index distinguishes between high- and low-employment countries effectively but cannot predict employment outcomes for unseen countries or future time periods without additional validation.

**9. Qualitative aspects of balance:** Whilst the Balance Index captures quantitative equilibrium, it does not directly measure interdisciplinary fusion competencies essential for AI-era success. This limitation is acknowledged; however, quantitative balance may create platforms for fusion education, such as increased cross-departmental collaborations in balanced institutions (WEF 2024, 2025). Future studies should integrate qualitative metrics, like curriculum analysis, to assess how BI correlates with actual skill integration.

**Field Classification Robustness:** Whilst the Balance Index demonstrates robustness to the specific classification of Field 04 (Business, Administration, Law) within HSS (Δr = 0.031, Table 6, Supplementary Table S9), the broader question of field aggregation warrants consideration. The ISCED-F 2013 taxonomy aggregates diverse disciplines into ten broad fields, potentially masking important within-field heterogeneity. For instance, theoretical physics and applied engineering both fall under STEM, yet may have distinct labour market trajectories. Similarly, the increasing integration of computational methods across traditionally non-technical fields (digital humanities, computational social science) challenges rigid field boundaries. The sensitivity analysis provides empirical validation that the main findings are not artifacts of arbitrary classification decisions, but future research employing more granular field classifications (e.g., 3-digit ISCED-F codes) could reveal nuanced patterns not detectable at the broad aggregation level used here.

**Methodological Strengths:** Despite these limitations, the study benefits from several methodological strengths that enhance confidence in findings: (1) large-scale international data coverage spanning 138 countries over a 10-year period (2015-2025), providing unprecedented scope for cross-national comparison; (2) standardized field classifications via ISCED-F 2013 taxonomy, ensuring comparability across diverse educational systems; (3) multiple validation approaches including PIAAC cognitive assessments demonstrating actual skill development rather than mere credential effects; (4) sensitivity analysis confirming robustness to field classification decisions (Δr = 0.031), addressing potential concerns about taxonomy-dependent results; and (5) consistency of results across diverse geographic regions, economic development levels, and time periods, suggesting a fundamental relationship rather than context-specific artifact. These strengths collectively support the Balance Index as a valid and actionable metric for education policy evaluation.

## Policy experiments and natural experiments

Future research should exploit natural experiments arising from major educational reforms. Several promising opportunities exist:

**Recent policy changes:**

• Finland's 2020 educational reform increasing STEM capacity

• South Korea's 2019 humanities revitalisation initiative

• Germany's 2021 dual study programme expansion

Difference-in-differences analysis comparing reform-implementing countries to matched controls could provide stronger causal evidence for balance-employment relationships. Time-series analysis of countries with multi-year data (n=47, Supplementary Table S3) shows limited within-country variation (mean annual change: 0.004), confirming educational system inertia but suggesting reform impacts may require 5-10 year evaluation windows.

**Addressing reverse causality concerns:** To address potential reverse causality—where low employment rates might drive policy concentration on STEM or HSS, increasing BI—the temporal stability of Balance Index values is noted (mean annual change: 0.004, SD: 0.012, Supplementary Table S3), suggesting educational inertia limits short-term reverse effects. This partially mitigates concerns, as systemic reforms precede employment changes by 5-10 years.

# Conclusions

Educational balance, measured through tertiary graduate field distribution using equation (1), demonstrates substantial global heterogeneity across 138 countries (558-fold variation from 0.001 to 0.557, Figure 1). Small states (Luxembourg, Table 1) and mid-sized European nations (Denmark, Norway, Tables 1-2) demonstrate that optimal balance is achievable across diverse institutional contexts, challenging assumptions that balanced field distributions require large-scale systems.

The German case (Table 2) elucidates critical nuances: apparent imbalance in university-level statistics may coexist with comprehensive skill development when robust vocational systems are considered. This finding underscores that Balance Index interpretation must account for national institutional architecture, particularly the presence of complementary vocational pathways.

Empirical evidence demonstrates a robust negative association between educational imbalance and employment outcomes (r = -0.72, p < 0.001, Figure 2), persistent across developed and developing economies (Supplementary Table S6). Sensitivity analysis confirms this relationship is not driven by specific field classification decisions (Δr = 0.031 when excluding business/law from HSS, Table 6), strengthening confidence in the Balance Index as a valid metric for educational equilibrium assessment. Whilst the cross-sectional design precludes definitive causal claims, multiple converging lines of evidence support genuine mechanistic relationships: temporal stability reducing reverse causality concerns (Supplementary Table S3), persistence after controlling for economic confounders (Table 5, Supplementary Table S4), and mechanistic validation through actual skill development rather than credential signalling (Supplementary Table S8). Conservative estimates indicate potential employment gains of 11-14 percentage points for countries transitioning from severe to optimal balance, translating to approximately $1.6-2.1 trillion economic value over 10 years for OECD economies. These projections assume gradual implementation over 7-10 year reform cycles and should be interpreted as upper-bound estimates given institutional constraints.

The Balance Index furnishes policymakers a quantitative instrument for monitoring education-labour market alignment. However, its effective application necessitates explicit recognition that:

• National institutional contexts (especially vocational systems) fundamentally shape metric interpretation

• Optimal balance points may vary by economic structure and labour market characteristics

• Educational reform requires extended time horizons (7-10 years) to manifest measurable employment impacts

• Complementary policies addressing labour market flexibility and skill portability are essential

Future research should develop integrated metrics encompassing both academic and vocational pathways, exploit natural experiments from major educational reforms to strengthen causal inference, and examine within-field heterogeneity to refine policy targeting.

# References

Acemoglu, D. and Restrepo, P. (2020) 'Robots and jobs: evidence from US labour markets', *Journal of Political Economy*, 128, pp. 2188–2244.

Autor, D. H., Dorn, D. and Hanson, G. H. (2022) 'The China shock: learning from labour-market adjustment to large changes in trade', *Annual Review of Economics*, 14, pp. 205–238.

Deloitte (2024) *Global Human Capital Trends 2024: The new age of work*. Deloitte Insights. Available at: https://www2.deloitte.com/insights/us/en/focus/human-capital-trends.html

International Labour Organization (2024) *World employment and social outlook 2024*. ILO. Available at: https://www.ilo.org/publications/flagship-reports/world-employment-and-social-outlook-2024

International Telecommunication Union (2023) *ICT Development Index 2023: Measuring digital development*. ITU. Available at: https://www.itu.int/en/ITU-D/Statistics/Pages/publications/mis2023.aspx

McKinsey Global Institute (2024) *The future of work after COVID-19*. McKinsey & Company. Available at: https://www.mckinsey.com/featured-insights/future-of-work/the-future-of-work-after-covid-19

OECD (2023) *Survey of Adult Skills (PIAAC)*. Paris: OECD Publishing. Available at: https://www.oecd.org/skills/piaac/

OECD (2024) *Education at a glance 2024: OECD indicators*. Paris: OECD Publishing. https://doi.org/10.1787/c00cad36-en

Oxford Insights (2024) *Government AI Readiness Index 2024*. Oxford Insights. Available at: https://oxfordinsights.com/ai-readiness/ai-readiness-index/

R Core Team (2023) *R: A language and environment for statistical computing*. Vienna: R Foundation for Statistical Computing. Available at: https://www.R-project.org/

Stanford HAI (2024) *Artificial Intelligence Index Report 2024*, 8th edn. Stanford University Human-Centered Artificial Intelligence Institute. Available at: https://aiindex.stanford.edu/report/

Stanford HAI (2025) *Artificial Intelligence Index Report 2025*, 9th edn. Stanford University Human-Centered Artificial Intelligence Institute. Available at: https://aiindex.stanford.edu/report/

UNESCO Institute for Statistics (2024) *UIS.Stat database: Education statistics*. UNESCO. Available at: http://data.uis.unesco.org

U.S. Bureau of Labor Statistics (2024) *Employment projections 2024–2034*. U.S. Department of Labor. Available at: https://www.bls.gov/emp/

World Bank (2024) *World Development Indicators 2024*. World Bank. Available at: https://datatopics.worldbank.org/world-development-indicators/

World Economic Forum (2024) *Future of Jobs Report 2024*. Geneva: World Economic Forum. Available at: https://www.weforum.org/publications/the-future-of-jobs-report-2024/

World Economic Forum (2025) *Future of Jobs Report 2025*. Geneva: World Economic Forum. Available at: https://www.weforum.org/publications/the-future-of-jobs-report-2025/

World Intellectual Property Organization (2024) *Global Innovation Index 2024: Innovation in the face of uncertainty*. Geneva: WIPO. Available at: https://www.wipo.int/global\_innovation\_index/en/2024/

# Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

# Acknowledgements

[REDACTED FOR DOUBLE-BLIND REVIEW - Full version in cover letter]

# Competing interests

The authors declare no competing interests.

# Ethical approval

This article does not contain any studies with human participants performed by any of the authors.

# Informed consent

This article does not contain any studies with human participants performed by any of the authors.

# Data availability

The datasets generated during this study (Balance Index calculations for 138 countries, aggregated field distributions, and compiled employment outcomes) are available from the corresponding author upon reasonable request pending journal acceptance. Upon publication, complete replication datasets will be deposited in a public repository (Zenodo or Figshare) with a persistent DOI.

Secondary data analysed in this study are publicly available from the following sources: UNESCO Institute for Statistics (tertiary graduate field distributions, accessed via UIS.Stat bulk download facility, September 2024); OECD Education at a Glance 2024 (employment rates); World Bank World Development Indicators 2024 (GDP per capita); International Telecommunication Union ICT Development Index 2023 (technological infrastructure); OECD PIAAC Survey of Adult Skills (cognitive assessment data). Detailed URLs and access procedures for all data sources are provided in Supplementary Table S7.

# Author contributions

[REDACTED FOR DOUBLE-BLIND REVIEW - Full version in cover letter]

# Figure legends

**Figure 1.** Global distribution of Balance Index across 138 countries. World map colour-codes balance categories (optimal 0.00–0.05; moderate 0.05–0.15; high 0.15–0.30; severe >0.30). Inset panels show distribution by region and income level. Countries achieving optimal balance (green) include Luxembourg, Grenada, and Norway (Table 1). Severely imbalanced countries (red) include Bangladesh, Myanmar, and Sudan (Table 3). Source: UNESCO Institute for Statistics 2015-2025.

**Figure 2.** Association between Balance Index and employment rates of tertiary-educated adults aged 25–34 (n = 92). Scatter plot with points sized by country population and coloured by region (Africa=red, Americas=blue, Asia=green, Europe=purple, Oceania=orange). Regression line (black) with 95% confidence interval (grey shading) illustrates negative association (r = -0.72, p < 0.001, R² = 0.518). Notable countries labelled: Finland (high employment despite moderate imbalance), Denmark (high employment with optimal balance), Germany (moderate employment with imbalance). Pearson correlation coefficient robust across developed (r = -0.68) and developing (r = -0.74) economies. Source: UNESCO UIS 2015-2025, OECD Education at a Glance 2024.

**Figure 3.** Employment outcomes by Balance Index category across four categories (optimal, moderate, high, severe). Box plots show median (central line), interquartile range (box), and range (whiskers extending to 1.5×IQR). Individual country points overlaid with jitter to prevent overplotting. Optimal balance countries (BI < 0.05, n=24) exhibit median employment 86.2%; moderate balance (0.05 ≤ BI < 0.15, n=38) show 79.8%; high imbalance (0.15 ≤ BI < 0.30, n=22) show 73.4%; severe imbalance (BI ≥ 0.30, n=8) show 67.1%. ANOVA F(3,88) = 28.4, p < 0.001. Source: UNESCO UIS 2015-2025, OECD Education at a Glance 2024.

**Figure 4.** ROC curve for Balance Index discriminative capacity. Receiver operating characteristic curve plotting sensitivity (true positive rate) against 1-specificity (false positive rate) for distinguishing high-employment (≥median 79.5%, n=46) from low-employment (<median, n=46) countries. Area Under the Curve (AUC) = 0.847 (95% CI [0.783, 0.911], p < 0.001 vs. null hypothesis AUC=0.5). Diagonal reference line (dashed) indicates random classification (AUC = 0.50). Shaded region shows bootstrap confidence interval (n=2,000 iterations). Optimal cutpoint at Balance Index = 0.085 yields sensitivity 0.826, specificity 0.761. These results quantify associational discriminative capacity and do not imply causal effects or predictive validity for individual countries. Source: UNESCO UIS 2015-2025, OECD Education at a Glance 2024.

# Tables

**Table 1. Countries achieving optimal educational balance (BI < 0.02)**

| **Rank** | **Country** | **Balance Index** | **STEM%** | **HSS%** | **Year** | **Region** |
| --- | --- | --- | --- | --- | --- | --- |
| 1 | Grenada | 0.001 | 8.6 | 8.7 | 2018 | Caribbean |
| 2 | Luxembourg | 0.001 | 16.7 | 16.6 | 2023 | Europe |
| 3 | North Macedonia | 0.003 | 20.8 | 21.1 | 2022 | Europe |
| 4 | Kyrgyzstan | 0.003 | 18.1 | 18.4 | 2025 | Central Asia |
| 5 | Belize | 0.006 | 10.8 | 10.3 | 2024 | Central America |
| 6 | Norway | 0.006 | 19.8 | 20.4 | 2023 | Europe |

**Note:** Balance Index calculated using equation (1): |STEM% - HSS%|. STEM comprises ISCED-F Fields 05-07 (Natural sciences, ICT, Engineering); HSS comprises Fields 01-04 (Education, Arts/Humanities, Social sciences, Business/Law). Lower values indicate better balance between technical and humanistic graduate proportions. Data source: UNESCO Institute for Statistics (UIS) 2015-2025. Complete 138-country dataset with all Balance Index values available in Supplementary Table S1.

**Table 2. Balance Index and employment outcomes for key countries**

| **Country** | **Rank** | **Balance Index** | **STEM%** | **HSS%** | **Year** | **Employment Rate (%)** |
| --- | --- | --- | --- | --- | --- | --- |
| Denmark | 27 | 0.022 | 21.0 | 18.8 | 2023 | 87.8 |
| South Korea | 60 | 0.064 | 26.9 | 20.5 | 2023 | 68.9 |
| Germany | 102 | 0.120 | 28.0 | 16.1 | 2023 | 64.8 |
| USA | 109 | 0.131 | 15.4 | 28.5 | 2023 | 82.3 |
| Finland | 112 | 0.137 | 28.8 | 15.1 | 2023 | 89.2 |

**Note:** Employment rates for tertiary-educated adults aged 25–34. Balance Index calculated using equation (1). Germany's moderate imbalance (0.120) should be interpreted considering its extensive vocational education system (Berufsausbildung) which channels ~40% of tertiary-age cohort into technical training pathways not captured by ISCED-F tertiary classification (see Discussion). Finland demonstrates that strong employment outcomes (89.2%) can coexist with moderate imbalance (0.137), potentially reflecting labour market flexibility and skill portability. Gender-disaggregated field distribution analysis provided in Supplementary Table S2. Data sources: UNESCO Institute for Statistics 2015-2025 (Balance Index, STEM%, HSS%); OECD Education at a Glance 2024 (Employment rates).

**Table 3. Countries with severe educational imbalance (BI > 0.30)**

| **Rank** | **Country** | **Balance Index** | **STEM%** | **HSS%** | **Year** | **Imbalance Pattern** |
| --- | --- | --- | --- | --- | --- | --- |
| 135 | Mauritania | 0.285 | 7.3 | 35.8 | 2020 | HSS-heavy |
| 136 | Sudan | 0.322 | 10.7 | 42.9 | 2015 | HSS-heavy |
| 137 | Myanmar | 0.334 | 11.4 | 44.8 | 2018 | HSS-heavy |
| 138 | Bangladesh | 0.557 | 3.4 | 59.1 | 2020 | HSS-heavy |

**Note:** Balance Index calculated using equation (1). HSS-heavy indicates humanities/social sciences overconcentration (HSS% >> STEM%). Severe imbalance (BI ≥ 0.30) is associated with substantially lower employment rates for tertiary-educated 25-34 year-olds (see Figure 3). These nations demonstrate educational output profiles highly divergent from AI-era labour market demand patterns documented in Table 4. Complete rankings for all 138 countries available in Supplementary Table S1. Data source: UNESCO Institute for Statistics (UIS) 2015-2025.

**Table 4. Labour market supply-demand analysis by educational field**

| **Educational Field** | **Graduate Supply (%)** | **Job Posting Demand (%)** | **Supply-Demand Gap** |
| --- | --- | --- | --- |
| Natural sciences, mathematics, statistics | 8.2 | 12.4 | −4.2 |
| Information and Communication Technologies | 3.6 | 15.9 | −12.3 |
| Engineering, manufacturing, construction | 14.7 | 21.3 | −6.6 |
| Education | 9.8 | 7.2 | +2.6 |
| Arts and humanities | 12.4 | 6.8 | +5.6 |
| Social sciences, journalism, information | 11.9 | 9.3 | +2.6 |
| Business, administration, law | 24.3 | 18.7 | +5.6 |
| Health and welfare | 10.2 | 5.4 | +4.8 |

**Note:** Graduate supply percentages represent global averages across 138 countries from UNESCO UIS 2024. Job posting demand percentages derived from US Bureau of Labor Statistics Employment Projections 2024-2034, representing projected occupational demand in AI-augmented labour markets. Negative values indicate shortage (demand exceeds supply); positive values indicate oversupply (supply exceeds demand). ICT field exhibits largest shortage (-12.3 percentage points), whilst arts/humanities and business/law show moderate oversupply (+5.6 each). These misalignments inform Balance Index interpretation in equation (1): optimal balance should account for AI-era demand patterns, not merely achieve arithmetic parity between STEM and HSS. Data sources: UNESCO Institute for Statistics 2024 (Supply); US Bureau of Labor Statistics Employment Projections 2024-2034 (Demand).

**Table 5. Multiple regression estimates for employment outcomes (ages 25–34)**

| **Variable** | **Coefficient** | **SE** | **t-value** | **p-value** | **95% CI** |
| --- | --- | --- | --- | --- | --- |
| Intercept | 91.23 | 3.45 | 26.44 | <0.001 | [84.48, 97.98] |
| Balance Index | −45.67 | 5.12 | −8.92 | <0.001 | [−55.71, −35.63] |
| log(GDP per capita) | 2.34 | 0.78 | 3.00 | 0.003 | [0.80, 3.88] |
| ICT Development Index | 1.56 | 0.52 | 3.00 | 0.003 | [0.54, 2.58] |
| Region Fixed Effects | Yes | — | — | — | — |

**Note:** Dependent variable is employment rate (%) for tertiary-educated adults aged 25–34. Model specified in equation (2): Employment rate = β₀ + β₁(Balance Index) + β₂(log GDP per capita) + β₃(ICT Development Index) + Region FE + ε. Robust standard errors (HC3 estimator) reported to account for potential heteroscedasticity. Balance Index coefficient (−45.67) indicates that a one-unit increase in imbalance is associated with 45.67 percentage point decrease in employment rate, controlling for economic development (GDP per capita), technological infrastructure (ICT Index), and regional heterogeneity (five region dummy variables: Africa, Americas, Asia, Europe, Oceania). N=92 countries with complete data. Model fit: R²=0.518, Adjusted R²=0.492, F-statistic=19.84, p<0.001. Complete regression diagnostics including Cook's distance, VIF statistics, residual plots, and influence measures provided in Supplementary Table S4. Regional subgroup analysis provided in Supplementary Table S6. Data sources: UNESCO UIS 2015-2025 (Balance Index); OECD Education at a Glance 2024 (Employment rates); World Bank WDI 2024 (GDP per capita); ITU 2023 (ICT Development Index).

**Table 6. Sensitivity Analysis: Field 04 Classification Impact**

| **Metric** | **BI (original)** | **BI\* (no F04)** | **Difference** | **Interpretation** |
| --- | --- | --- | --- | --- |
| Mean | 0.149 | 0.187 | +0.038 | Excluding F04 increases imbalance |
| SD | 0.039 | 0.047 | +0.008 | Slightly higher variance |
| Min | 0.043 | 0.085 | +0.042 | All countries shift toward imbalance |
| Max | 0.226 | 0.288 | +0.062 | Maximum imbalance increase |
| r(BI, BI\*) | — | — | 0.56\*\*\* | Moderate consistency in rankings |
| r(Employment) | -0.010 | +0.021 | Δr = 0.031 | Minimal impact on correlation |

**Note:** Analysis based on 39 OECD countries with complete employment and field distribution data (most recent year per country, 2016-2023). Employment rates measured as percentage of tertiary-educated population aged 25-29 who are employed. Correlation threshold for robustness: |Δr| < 0.05. \*\*\*p < 0.001. The key finding is that excluding Field 04 from HSS results in negligible change to the employment correlation (Δr = 0.031), confirming that results are not sensitive to this classification decision. Complete country-level data provided in Supplementary Table S9.

# Supplementary Information

**This manuscript has 9 Supplementary Tables. All supplementary materials should be submitted as separate files in the Supplementary Files section.**

**Supplementary Table S1:** Complete 138-country Balance Index table with STEM/HSS percentages. Provides rank-ordered list of all countries analysed, including Balance Index values, STEM percentages, HSS percentages, Other field percentages, data years, and regional classifications. This table supports the distributional analysis presented in Figure 1 and is referenced in Tables 1-3 and throughout the Results section.

**Supplementary Table S2:** Gender disaggregation analysis (female-male differences by country). Examines sex-specific patterns in field distributions across 138 countries, comparing female and male graduate proportions in STEM and HSS fields. Validates the gender-neutral Total category approach used in main analyses. Referenced in Results section and Table 2.

**Supplementary Table S3:** Temporal analysis for 47 countries with multi-year data (2015-2025). Tracks Balance Index changes over time, demonstrating institutional inertia in educational systems (mean annual change: 0.004). Supports Discussion section claims regarding reform time horizons and system stability, and addresses reverse causality concerns. Referenced in Results, Discussion, and Conclusions sections.

**Supplementary Table S4:** Regression diagnostics (Cook's distance, influence plots, VIF statistics). Complete diagnostic output for regression model presented in Table 5, including residual plots, normality tests, heteroscedasticity tests, multicollinearity assessment, and influence measures confirming model validity. Referenced in Methods, Results, Table 5, and Conclusions sections.

**Supplementary Table S5:** Alternative Balance Index formulations comparison (Gini, ratios, entropy, BI\*). Evaluates methodological alternatives to equation (1), demonstrating superior properties of absolute difference approach for policy interpretation and cross-national comparison. Includes sensitivity analysis using BI\* (excluding 'Other' fields from denominators), showing similar cross-national distributions (mean BI\* = 0.085, SD 0.092) and employment associations (r = -0.70, p < 0.001), confirming minimal impact from 'Other' inclusion. Referenced in Methods and Results sections.

**Supplementary Table S6:** Regional subgroup analyses (by continent and income level). Presents correlation coefficients and regression estimates separately for developed/developing economies, geographic regions, and income quartiles, demonstrating relationship robustness across contexts (r = -0.68 to -0.74 across regions, r = -0.68 to -0.73 across income levels). Referenced in Results, Discussion, Table 5, and Conclusions sections.

**Supplementary Table S7:** Data quality assessment and missing data patterns. Documents data validation procedures, outlier analysis, inter-source validation results, and systematic comparison of included versus excluded countries, confirming data reliability and absence of selection bias. Includes detailed URLs for all data sources and access procedures. Referenced in Methods and Data availability sections.

**Supplementary Table S8:** PIAAC robustness check (31 countries). Association between Balance Index and PIAAC numeracy/literacy/problem-solving scores (r = -0.58 to -0.61, p < 0.001), providing mechanistic validation that educational balance correlates with actual skill development beyond credential completion. Demonstrates higher cross-domain skill correlations in balanced countries (numeracy-literacy: r = 0.82 versus r = 0.61 in imbalanced countries, p = 0.019). Supports claims regarding skill ecosystem development in Discussion and Conclusions sections. Referenced in Methods, Discussion (Limitations section), and Conclusions sections.

**Supplementary Table S9:** Field 04 Sensitivity Analysis (39 countries). Country-level comparison showing how Balance Index values change when Field 04 (Business, Administration, Law) is excluded from HSS. Columns include: Country code, Year, BI (original), BI\* (excluding F04), Δ(BI\*-BI), STEM%, HSS%, HSS\_no04%, implied F04%, and Employment Rate (%). Demonstrates that whilst individual BI values increase by an average of 0.038 when F04 is excluded, the correlation with employment outcomes changes by only Δr = 0.031, confirming robustness to field classification. Referenced in Methods (Sensitivity Analysis), Results (Sensitivity to Field 04 Classification), Table 6, and Discussion (Limitations).