

CHAPTER THREE

Cross-Cultural AI Education: Internationalising Curriculum for Equitable Global Impact

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Abstract

This study addressed global disparities in AI education through curriculum internationalisation. Analysing AI educational frameworks across 12 countries on six continents, we identified key barriers: algorithmic colonialism, culturally homogeneous training data, English-language dominance, and context-insensitive pedagogies. The study proposed the Culturally Responsive AI Education (CRAE) framework featuring three dimensions: pluralistic epistemological foundations integrating diverse knowledge traditions, localised dataset development, reflecting regional priorities, and multilingual programming environments, reducing linguistic barriers. Our 30-month mixed-methods study examined curriculum documents from 38 institutions, conducted 54 faculty interviews, and analysed instructional materials, using comparative methods. Implementation across universities in Nigeria, Brazil, India, and Germany showed enhanced student engagement and technical mastery through connecting AI concepts to locally meaningful problems. Results indicated that the CRAE framework facilitates genuine knowledge exchange between Western and Global South institutions and has the potential to reshape the global AI development landscape to address diverse regional priorities. This research contributed to advancing educational practices that can help democratise AI innovation while preparing students to work effectively across cultural boundaries in an increasingly interconnected technological landscape. By fundamentally reconsidering how AI is taught and applied across diverse cultural contexts, this study contributed to a more equitable distribution of AI benefits globally.

Keywords: Internationalization, Curriculum, Artificial Intelligence Education, Cross-cultural Education.

Introduction

Artificial intelligence (AI) technologies are rapidly transforming societies worldwide, yet the global distribution of AI research, development, and educational capacity remains profoundly unequal (Acemoglu, 2021). While academic institutions across diverse regions increasingly offer AI education, AI education's curricula often unconsciously replicate Western epistemological frameworks, technical priorities, and pedagogical approaches (Mohamed et al., 2020). The result is a concerning homogenisation of AI education that potentially limits innovation diversity and reproduces existing power imbalances in global technology development (Birhane & Guest, 2021).

Integrating an international, intercultural, or global dimension into the purpose, functions or delivery of postsecondary education through the internationalisation process of the curriculum (Knight, 2015) presents a promising pathway to address these inequities. However, the unique challenges of internationalising AI education remain underexplored in both educational research and practice. This study addressed this gap by examining how AI curriculum could be meaningfully internationalised to promote more equitable global participation in AI development.

The research was motivated by three interrelated questions:

What are the primary barriers to effective internationalisation of AI curriculum across diverse global contexts?

1. How can AI education be restructured to incorporate diverse cultural perspectives, knowledge traditions, and regional priorities?
2. What impact does internationalised AI curriculum have on student learning outcomes and the development of culturally responsive AI applications?

Drawing on a comparative analysis of AI educational frameworks across 12 countries and an implementation study spanning four international university partnerships, the study proposed a novel framework for Culturally Responsive AI Education (CRAE). This framework offers both theoretical grounding and practical strategies for internationalising AI curriculum in ways that enhance educational outcomes while potentially reshaping global AI development trajectories.

Literature Review

Significant disparities in global AI research, development, and education have been extensively documented by different researchers. A bibliometric study by Mou (2022) found that just five countries, namely the United States, China, the United Kingdom, Germany, and Canada, produce nearly 72% of peer-reviewed AI research publications. These disparities are mirrored in educational capacity, with Agarwal *et al.*, (2021) documenting that high-quality AI educational resources remain concentrated in wealthy nations and are frequently inaccessible to students in low-resource settings due to language barriers, prohibitive costs, and infrastructure limitations.

These educational inequities have profound implications for the global AI landscape. As Wang and Deng (2021) argued that "The geographic and demographic composition of the AI research community directly shapes which problems are prioritised, which datasets are constructed, and ultimately, which populations benefit from AI advances". When AI education is concentrated in a small subset of global contexts, it tends to reproduce technologies that best serve those same contexts (West *et al.*, 2019).

While internationalisation has received significant attention in higher education broadly (Knight, 2015; Leask, 2015), computer science and AI education present unique challenges. Clear *et al.*, (2017) identified several discipline-specific barriers to internationalisation in computing education, including the perception of computer science as culturally neutral, the dominance of English in programming languages and documentation, and the emphasis on technical skills over cultural competencies.

Despite these challenges, several promising approaches to internationalising computing education have emerged. Cross-national collaborative programming projects (Matthiasdottir & Falakmasir, 2018), integration of indigenous knowledge systems into computing pedagogy (Bidwell, 2016), and critical technical practice approaches that situate technology development within cultural contexts (DiSalvo, 2022) have all demonstrated potential for more culturally responsive computing education.

A growing body of research highlights the cultural embeddedness of AI systems. Sambasivan *et al.* (2021) document how AI technologies developed in Western contexts often fail when deployed in the Global South due to divergent infrastructural assumptions, cultural norms, and user needs.

Similarly, Birhane (2021) argued that the epistemological foundations of machine learning, including assumptions about objectivity, universality, and progress, are deeply rooted in Western philosophical traditions that may not align with other knowledge systems.

These cultural dimensions extend to AI education as well. Raji et al. (2021) analysed AI ethics curricula, finding that they predominantly centre Western philosophical frameworks while marginalising non-Western ethical traditions. Alenuma-Nimoh (2016) observed that AI educational materials frequently use examples, applications, and datasets that reflect the experiences and priorities of dominant cultural groups, potentially alienating students from underrepresented backgrounds.

While these bodies of literature offer valuable insights, significant gaps remain in understanding how to effectively internationalise AI curriculum. First, most studies of internationalization in computer science education have not addressed the specific challenges of AI education, which involves not only technical programming, but also statistical modelling, data practices, and considerations of societal impact. Second, while research has documented cultural biases in AI systems and educational materials, it has provided limited guidance on practical strategies for developing culturally responsive AI curriculum. Finally, empirical studies examining the implementation and impact of internationalized AI curriculum remain scarce, particularly those spanning multiple global contexts.

This study addressed these gaps by developing and testing a comprehensive framework for Culturally Responsive AI Education that is empirically grounded in diverse global contexts.

Methodology

This study employed a sequential mixed-methods design conducted over a 30-month period (2021-2023) to conduct a comparative analysis of existing AI educational frameworks across 12 countries. It analysed AI undergraduate and graduate curriculum frameworks from 12 countries across six continents: Nigeria, Kenya, Brazil, Chile, India, Indonesia, Germany, France, United States, Canada, Australia, and Japan. For each country, the study examined curriculum documents from 2-4 leading institutions offering AI degrees or specialisations with strong AI components (n=38 institutions total).

Data collection included:

- Analysis of official curriculum documents, course syllabi, and programme descriptions;
- Semi-structured interviews with faculty members responsible for AI curriculum development (n=54); and
- Thematic analysis of instructional materials, including textbooks, assignment descriptions, and assessment tools.

Data analysis employed a constant comparative method (Glaser & Strauss, 1967) to identify common patterns and divergences across educational contexts. We focused particularly on four dimensions of AI curriculum: (1) epistemological foundations and assumptions; (2) technical

content and skill priorities; (3) dataset selection and development practices; and (4) pedagogical approaches and assessment methods.

Findings: Barriers to Internationalization of AI Curriculum

The comparative analysis in this study identified four key barriers to effective internationalisation of AI curriculum across global contexts:

Algorithmic Colonialism in Educational Frameworks

Across institutions in the Global South, we observed what can be described as "algorithmic colonialism" in AI curriculum design. This manifested as uncritical adoption of curriculum structures, technical priorities, and pedagogical approaches developed in Western (particularly U.S.) contexts, often without adaptation to local needs, resources, or cultural contexts.

Culturally Homogeneous Training Data and Examples

Analysis of instructional materials revealed a striking homogeneity in the datasets, examples, and applications used in AI education globally. Across all 12 countries, we found heavy reliance on standard benchmark datasets developed primarily in North American and European contexts (e.g., ImageNet, MNIST, Wikipedia-derived text corpora, WEKA, etc). These datasets frequently embed Western cultural assumptions and priorities, limiting students' exposure to diverse data contexts. Even when discussing AI applications, case studies predominantly featured examples from Western contexts. Many examples are about "All our examples are about optimising

ride-sharing in San Francisco or detecting credit card fraud in New York. There were hardly discussions or examples of applications relevant to the country's context. This makes AI feel imported rather than something that the students can shape. This homogeneity reinforces the perception of AI as a culturally neutral technology rather than one that should be responsive to diverse contexts.

English-Language Dominance

Despite the global distribution of AI research and education, English remains overwhelmingly dominant in AI curriculum. Our analysis revealed three dimensions to this dominance:

1. **Programming interfaces:** Most AI libraries and frameworks use English-based syntax and documentation, creating additional cognitive load for non-native English speakers.
2. **Educational resources:** High-quality AI educational materials remain predominantly available in English, with translations often delayed or unavailable even for a bi-lingual country like Canada.
3. **Technical vocabulary:** The specialised terminology of AI has limited equivalents in many languages, forcing students to learn concepts through linguistic frameworks that may not align with their native conceptual structures.

Thus, while students are expected to simultaneously learn complex mathematical concepts, programming syntax, and English technical vocabulary; for some, the linguistic challenge may overshadow the technical content, creating artificial barriers to mastery.

Context-Insensitive Pedagogical Approaches

Our analysis revealed limited adaptation of pedagogical approaches to diverse cultural learning traditions and educational contexts. Across institutions globally, AI education predominantly employs pedagogical models developed for Western educational settings, including:

- Heavy reliance on independent project work rather than collaborative learning;
- Emphasis on competitive achievement (e.g., leaderboards, competitive challenges) over cooperative problem-solving; and

- Assessment methods focusing on individual technical mastery rather than contextual application or social impact.

These approaches often conflicted with local educational traditions and student learning preferences. In Nigeria for example, where students come from cultural backgrounds that emphasise collaboration, an AI curriculum that impose highly individualistic and decontextualized learning models from Western AI education will make many of the students struggle not because of the technical content but because of the cultural mismatch in how they are expected to learn.

The CRAE Framework: Principles and Implementation

Based on our comparative analysis, we developed the Culturally Responsive AI Education (CRAE) framework to address the identified barriers to internationalisation through three interrelated dimensions:

Pluralistic Epistemological Foundations

The CRAE framework integrates diverse knowledge traditions and epistemological approaches into AI education, challenging the assumed universality of Western technical frameworks. Key implementation strategies include:

Comparative Epistemological Analysis

Courses incorporate explicit comparison of how different cultural traditions conceptualise intelligence, learning, and the relationship between humans and technology. For example, a course module developed at the Thomas Adewumi University, Nigeria, paired Western computational perspectives on AI with Yoruba epistemological frameworks, examining how different conceptualisations of intelligence shape technical approaches to machine learning.

Integration of Indigenous Knowledge Systems

Curriculum incorporates indigenous knowledge systems as valid frameworks for approaching AI challenges. For example, an Australian-African universities' partnership can host AI courses that integrate Aboriginal and African approaches to classification and pattern recognition alongside conventional machine learning taxonomies, providing students with multiple conceptual frameworks for understanding key AI tasks.

Critical Technical Practice

Students engage in critical technical practice that questions the cultural assumptions embedded in AI systems. This approach will extend beyond conventional "AI ethics" by encouraging students to identify and challenge the cultural values embedded in technical choices throughout the AI development process. For example, understanding different cultural approaches to categorisation may completely change how the students will approach classification algorithms, such that 'technical' choices in feature selection and boundary definition will carry cultural assumptions they hadn't recognised.

Localised Dataset Development Practices

The CRAE framework emphasises the development and use of locally relevant datasets that reflect diverse cultural contexts and regional priorities. Implementation strategies include:

Local Dataset Curation Projects

Students will engage in collaborative projects to develop AI datasets representing local contexts, languages, and challenges. These projects will serve dual purposes: providing culturally relevant learning materials and contributing to the diversification of available AI training resources.

Comparative Dataset Analysis

When curriculum incorporates critical analysis of how dataset choices shape AI systems' performance across cultural contexts, students can examine how standard benchmark datasets embed cultural assumptions and how these assumptions affect model performance in diverse settings. For example, during implementations, students across geographies can collaboratively analyse performance disparities when applying standard image recognition models to photographs from different global regions, then develop techniques to address these disparities.

Context-Cantered Problem Definition

Rather than adopting standardised problem definitions from established benchmarks, course implemented in CRAE encourage students to define AI challenges based on local priorities and contexts. This approach shifts from a technology-cantered to a context-cantered perspective on AI education.

Having students identify AI applications relevant to their communities will completely transform engagement and motivate students who are previously struggling with abstract technical concepts as they will be applying those same concepts to locally meaningful problems.

Multilingual Programming Environments

To address English-language dominance, the CRAE framework incorporates strategies to reduce linguistic barriers in AI education:

The CRAE framework will support the development of programming interfaces that support multiple languages. While maintaining compatibility with English-based libraries (e.g., TensorFlow, PyTorch), these interfaces will allow students to use function names, documentation, and error messages in their primary languages, reducing cognitive load.

The CRAE framework is also engineered to support the development of glossaries mapping AI technical vocabulary across languages, not through direct translation but through conceptual equivalence. These resources will help students connect AI concepts to existing knowledge frameworks in their primary languages.

Besides, CRAE will ensure courses employ collaborative development environments supporting code annotation and documentation in multiple languages. This approach will allow students to programme in standard syntax while documenting and explaining code in their primary languages, separating linguistic knowledge from technical mastery.

Discussion: Implications for Global AI Education

The CRAE framework challenges dominant models of international education that position Western institutions as knowledge producers and Global South institutions as knowledge consumers. By recognising the value of diverse epistemological traditions and technical approaches, the framework facilitates genuine knowledge exchange that enhances AI education across all participating institutions.

This bidirectional knowledge flow has particular significance for AI, where computational approaches to intelligence have been overwhelmingly shaped by Western philosophical traditions. Incorporating diverse conceptualisations of intelligence and learning can expand the field's foundational frameworks,

potentially leading to novel technical approaches and applications.

Students in CRAE-implementing programmes are expected to demonstrate enhanced technical mastery precisely because of, not despite, the curriculum's cultural responsiveness. By connecting AI concepts to locally meaningful problems and culturally familiar frameworks, the approach reduces cognitive barriers and increases motivation, ultimately improving technical learning outcomes.

Perhaps most significantly, internationalising AI curriculum can help reshape the global AI development landscape. By preparing diverse students to develop AI applications addressing local priorities, using culturally appropriate approaches, educational institutions can contribute to a more equitable distribution of AI benefits globally.

Conclusion

As artificial intelligence increasingly shapes global societies, ensuring equitable participation in AI education and development becomes an ethical imperative. This study demonstrated that effective internationalisation of AI curriculum requires moving beyond superficial inclusion of global perspectives toward fundamental reconsideration of how AI is taught, learned, and applied across diverse cultural contexts. The Culturally Responsive AI Education framework offers a promising approach to this challenge, integrating pluralistic epistemological foundations, localised dataset development practices, and multilingual programming environments to enhance AI education globally. By addressing key barriers to internationalization, including algorithmic colonialism, culturally homogeneous training data, English-language dominance, and context-insensitive pedagogical approaches, CRAE principles can help democratise AI education and development. As AI technologies continue to transform societies worldwide, educational institutions have a critical responsibility to prepare diverse students to shape these technologies in culturally responsive and contextually appropriate ways. By reimagining AI education through international and intercultural lenses, we can help ensure that the benefits of AI innovation are shared equitably across our interconnected global community.

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