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Collaboration, Creativity and Compassion in a Digital Society

Enhancing cultural sensitivity in university artificial intelligence principles

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Universities' education-related artificial intelligence (AI) principles are vital statements outlining the institutions' stances towards the technology's use in learning. Ensuring the cultural sensitivity of these principles is vital given today's superdiversity in higher education. This paper presents insights from research examining these principles' cultural sensitivity, using Australian universities as its case study. In the research, 28 out of 42 universities' AI principles content was analysed using qualitative content analysis. The findings show that cultural sensitivity is generally addressed at a surface level. The paper argues that all universities not only need to provide robust, publicly accessible educational AI principles, but also actively integrate cultural sensitivity into the principles. A novel framework is provided to support this integration.

Keywords: artificial intelligence principles, cultural sensitivity, universities, policy decomplexification, case study, qualitative content analysis

Introduction

As artificial intelligence (AI) expands throughout higher education, universities face ongoing challenges in ensuring equity in AI implementation for diverse groups, particularly students. Higher education institutions, much like the Tech Giants themselves, continue to seek ways to reduce AI's cultural bias, as the technology poorly handles cultural distinctions, leading to "inaccurate, misleading, and sometimes harmful outcomes" for different populations (Wang et al., 2025). Cultural bias is a particular problem for international students, who are already underrepresented in higher education academic integrity policy (Bannister et al., 2024).

This paper focuses on universities' education-related AI principles, in understanding these principles' cultural sensitivity. The principles are vital statements that help students, staff and other stakeholders grasp the key aspects of an institution's stance on AI for learning. The paper deliberately does not focus on policy documents, due to their length and complexity; sets of principles, by contrast, usefully and efficiently help distil complex policies into understandable and actionable protocols. Groupings of institutional principles are a vital part of policy decomplexification: crucial in making major challenges more manageable (Eckerd, 2024).

The paper provides insights from an investigation into university education-related AI principles using two methods: a case study (of Australian universities) and qualitative content analysis (of their AI principles). The paper argues that all universities not only need to provide robust, publicly accessible educational AI principles, but also actively integrate cultural sensitivity into these principles. While AI equity is increasingly being examined in educational technology research (see, for example, Azevedo et al., 2026; Jin et al., 2025; Wang et al., 2023), AI principles' cultural sensitivity has not yet been considered. This paper helps fill the current gap.

Literature review

The existing literature, not only about higher education AI policy, but also cultural sensitivity (the paper's theoretical framework), continues to expand. This review examines these areas in succession.

AI policy in higher education

AI advancements are reshaping countless higher education activities. Students, educators and scholars are increasingly leveraging AI tools for learning, research and teaching (Henderson et al., 2025; Smith et al., 2026), creating new opportunities and challenges for universities (Chan, 2023; Jiang et al., 2025). Growing numbers of studies are consequently examining higher education institutions' AI policies and guidelines. Existing research has proposed comprehensive frameworks for university AI policy development (Chan, 2023), addressed academic integrity and ethics (Azevedo et al., 2026; Cotton et al., 2024; Smith et al., 2026), examined the

effectiveness of AI policies (Jiang et al., 2025) and mapped institutional AI policies across regions (Jin et al., 2025; Parker et al., 2025), finding not only that approaches range from prohibition to instructor discretion, but also that regional differences are shaped by socio-cultural and regulatory factors. To date, though, no research has examined higher education AI policy in relation to cultural sensitivity, to which this paper now turns.

Cultural sensitivity in higher education

While cultural sensitivity is widely used, it remains difficult to define. According to a leading definition, it can be understood as "the ability to recognize, understand and react appropriately to beliefs, values, norms, and behaviors" of individuals from different cultural or ethnic groups (Bobel et al., 2022, p. 372). The notion emphasises a person's ability to regulate thoughts and actions in response to culturally sensitive issues (Stone, 2006). Foronda (2008) identifies knowledge, consideration, understanding, respect and tailoring as cultural sensitivity's defining attributes, which are shaped by cultural diversity, the awareness of cultural difference and encounters with culturally different individuals: all later contributing to effective communication, more effective teaching and greater satisfaction between parties. Additional dimensions of cultural sensitivity – in particular, its applicability to surface structure versus deep structure (Resnicow et al., 1999) – have been examined over time, but the aforementioned key aspects continue to be widely used.

Cultural sensitivity is crucial given today's superdiversity in higher education. According to UNESCO (2026), over 7 million students are currently studying abroad globally. As such, universities are educating students from increasingly diverse linguistic, ethnic and socio-economic backgrounds. These students often encounter challenges ranging from language barriers to unfamiliar educational systems that impact their academic achievement (Wang et al., 2023). Universities are responding by applying cultural sensitivity to diverse areas, ranging from institutional policy to support services (Chen & Hu, 2023; Wang et al., 2023).

The existing scholarship has also examined cultural sensitivity in curricula, campus life and intercultural contact. For instance, Deardorff (2006) has argued that intercultural competence is a central outcome of internationalised higher education, noting that many institutions do not define or assess it clearly. Chen and Hu (2023) have found that students who have taken intercultural communication courses scored higher on interaction confidence and attentiveness, though such issues as language limitations remained barriers.

AI policy in higher education and cultural sensitivity

Generative AI's rise in higher education makes cultural sensitivity more urgent than ever before. While generative AI tools are often presented as scalable, personalised and efficient, they are not culturally neutral (Creely & Henderson, 2025). Indeed, they are trained on uneven datasets, shaped by dominant languages and interpreted through institutional rules (Herzog, 2025). AI tools often fail to recognise accents, dialects and multilingual writing practices, among others (Wang et al., 2023). Hence, Bannister et al. (2024) have called for more attention to universities' AI policies in relation to international students' needs. Policies and assessment rules can also unevenly affect Indigenous students, culturally and linguistically diverse learners, and students with unequal access to paid generative AI tools (Jiang et al., 2025; Liang et al., 2023; Lodge et al., 2025).

Higher education AI governance frameworks are beginning to respond to these challenges. McDonald et al. (2025) have found that university guidelines are becoming stronger, but many remain unclearly developed; STEM-related academic activities receive less explicit guidance, and roughly half of universities do not clearly address cultural, ethical or equity-related concerns. Jiang et al. (2025) have noted that students' perceptions of AI-related resources and policies differed significantly by discipline, gender and racial identity. Similarly, Parker et al. (2025) have found that institutional approaches vary across cultural and regulatory contexts, and often use broad ethical language. Jin et al. (2025) have also shown that universities across regions differ in emphasising innovation, regulation, equity and access. That is, AI policymaking in higher education needs to be guided by global standards while remaining sensitive to local cultural conditions (Jin et al., 2025).

Australian higher education is a prime example of AI policy evolution. Government authorities have issued several AI policies and frameworks since 2018 to guide educators and institutions (Li, 2025). The Australian Framework for Artificial Intelligence in Higher Education (Lodge et al., 2025) calls on institutions to address linguistic and cultural barriers to AI use, and to mitigate biases affecting marginalised groups. Drawing on the

CARE Principles (Carroll et al., 2020), it affirms Indigenous data sovereignty and knowledge, and recognises epistemological tensions between Indigenous ways of knowing and AI systems shaped by Western knowledge frameworks. These commitments are highly relevant to cultural sensitivity and epistemic justice. While the framework provides substantial support for cultural and linguistic equity, it does not use the term "cultural sensitivity" or connect its commitments to the cultural sensitivity literature (Lodge et al., 2025). Universities' AI policy or guidance approaches vary widely (Jin et al., 2025). They generally defer decisions to individual instructors, requiring students to follow course-specific guidance in course descriptions (Parker et al., 2025).

Thus, notable gaps appear in the existing scholarship. While research about AI in higher education has identified risks for diverse students, it has often focused on tools, access and academic integrity rather than cultural sensitivity. Previous policy studies have shown that university AI guidelines vary across cultural and regulatory contexts (Jin et al., 2025; Parker et al., 2025). However, there remains limited research about universities' approaches to cultural sensitivity in terms of AI principles. Hence, this study fills the gap in knowledge by asking the following overarching research question: How (if at all) do university AI principles address cultural sensitivity? The approaches used to answer this question are outlined in the next section.

Methodology and methods

The study employed a qualitative methodology and was situated within a constructivist paradigm, in which social meaning is constructed rather than discovered, and understanding requires interpreting the meanings that actors invest in their texts and practices (Creswell, 2003). This stance was appropriate because cultural sensitivity is a contested and value-laden concept; its presence in policy texts cannot simply be objectively counted, but rather must be interpreted through a theoretically informed lens. University AI principles are also socially constructed artifacts that encode institutional values and seek to shape stakeholders' behaviours. Therefore, analysing them requires attention to language, emphasis and framing (Bowen, 2009).

Two research methods were used, with the first being a case study (Yin, 2003). The investigation treated the Australian higher education sector as its case, encompassing the 42 Australian universities registered in the Tertiary Education Quality and Standards Agency's "Australian University" provider category (https://www.teqsa.gov.au/national-register). (The University of Adelaide and the University of South Australia were counted as Adelaide University). A case study was apt given the need for a contextualised, bounded understanding of phenomena (Yin, 2003). Australia's universities were deemed suitable because they operate in an internationalised context that values diversity. To ensure thoroughness, targeted Google searches were undertaken. The key search terms combined "AI/genAI principles" with the relevant university name (e.g., "AI principles, the University of Sydney"). The universities' websites were also searched carefully for education-related AI principles (and AI policy documents). The data were collected from 9 to 23 June 2026. Documents and webpage statements were included when they were publicly accessible, issued by the university and contained institutional principles or commitments concerning AI use in learning and teaching.

The second method was directed qualitative content analysis (Hsieh & Shannon, 2005). This approach was apt because the analysis was informed by the conception of cultural sensitivity from the literature review, while remaining open to themes emerging from the university AI principles. NVivo 15 was used to code and analyse the textual data. The codes were then assessed for their relevance to cultural sensitivity (as outlined in the literature review). This approach enabled the analysis to identify both the presence of cultural-sensitivity elements and the depth of universities' engagement with them. The next section outlines the research results. The distinction between AI principles and operational AI policies was assessed case by case, according to the content's function. Principles were understood as explicit institutional values or overarching commitments guiding AI use in education. These principles could appear in dedicated principles webpages, general organisational documents, policies, statements, guidelines or frameworks. Collateral in the latter group was included when it featured identifiable principle content; only that content was collected for analysis. Materials that did not articulate underlying institutional values or commitments – such as procedural instructions, assessment permissions, referencing requirements or misconduct processes – were excluded. The process was completed by the first author; another author reviewed the initial findings, in line with previous studies (see DeMeester et al., 2017; Lederer & Sheena, 2021) involving collaborative qualitative content analyses.

Universities are identified in the study to allow readers to trace all sources. The analysis reflects the collateral available during the collection period. It is worth noting that the study's purpose is sector improvement, not institutional criticism. No Indigenous colleagues contributed to developing or applying the Indigenous knowledges dimension of the analysis. The findings reflect the researchers' interpretations of public institutional statements. Future research should involve Aboriginal and Torres Strait Islander colleagues and communities. As the study used publicly accessible institutional documents, ethics approval was not required.

Findings

The universities' AI principles approach cultural sensitivity varyingly. The ensuing sections canvas the findings.

The landscape of AI principles in Australian universities

The existence of AI principles (hyperlinked in Table 1) differs across Australian universities. Table 1 classifies the universities by the form and accessibility of their principles. Out of 42 universities, 13 provide dedicated AI principles and 15 provide documents functioning as principles. These 28 universities form the content analysis sample. A further nine provide operational guidance or policies, three have principles that are not publicly accessible, and two have no identifiable AI principles.

Table 1
Classification of Australian universities by form and accessibility of AI principles

Category	Description	Universities
1. Dedicated AI principles (*n*=13)	A standalone document, section or webpage whose primary purpose is to outline the institution's AI principles.	Monash, Charles Darwin, James Cook, Charles Sturt, Victoria, UNSW, Melbourne, Sydney, ACU, Deakin, ANU, ECU, UTS
2. AI policies, statements, guidelines, or frameworks functioning as principles (*n*=15)	Documents/webpages titled otherwise (policy, guideline, framework, or "guardrails") that nonetheless outline values and commitments equivalent to principles; the principle content was extracted for analysis.	Macquarie, Federation, La Trobe, Newcastle, RMIT, Swinburne, Curtin, Queensland, Adelaide, UNE, USC, Canberra, Bond, Western Sydney, Southern Cross
3. Operational guidance and policies (*n*=9)	Public how-to or procedural material, or academic-integrity rules, with no clear underlying values; often devolved to the course-instructor level.	Central Queensland, Wollongong, Avondale, Flinders, Torrens Australia, Notre Dame Australia, Tasmania, Western Australia, Southern Queensland
4. Principles exist but are not publicly available (*n*=3)	AI principles were confirmed to exist but are accessible only behind an institutional login; they could not be analysed.	Murdoch, QUT, Griffith
5. No identifiable AI principles (*n*=2)	No clearly identifiable public AI principles located at the time of collection.	Australian University of Theology, University of Divinity

Engagement with cultural sensitivity

The 28 universities engage with cultural sensitivity in diverse ways. Three themes in their engagement are evident: (1) viewing AI as a matter of compliance and integrity (six universities); (2) discussing ethical values, but only addressing cultural issues in general terms (18 universities); and (3) meaningfully engaging with culture, particularly Indigenous knowledges (four universities). No university used the term "cultural sensitivity" in its AI principles; also, none used related terminology, such as "cultural competence" or "cultural capability."

Table 2
Classification of universities by overall depth of cultural engagement

Position on spectrum	Characteristics	Universities
Compliance/integrity	AI framed as governance, compliance, and academic integrity; little or no reference to culture.	ANU, Curtin, Adelaide, USC, Southern Cross, Canberra
Values, culturally generic	Ethical-values vocabulary (dignity, fairness, inclusion and anti-bias) layered over governance, but cultural differences engaged only in the abstract.	ACU, James Cook, Charles Sturt, Melbourne, Macquarie, RMIT, Federation, La Trobe, UNSW, UTS, Western Sydney, Newcastle, Edith Cowan University, Deakin*, Sydney, Swinburne, Victoria, Bond
Substantive cultural (Indigenous) engagement	Culture, and especially Indigenous knowledge and data sovereignty, engaged substantively and translated toward concrete commitment or action.	Monash, University of New England, Queensland, Charles Darwin

(*Note: Deakin provides strong representation and anti-bias prompts, but is silent on Indigenous knowledges and language)

The universities' engagement with specific cultural sensitivity elements also varies significantly. Table 3 shows engagement across four cultural sensitivity dimensions. In the table, "Substantive" indicates a clear principle-level commitment, position, statement or direction of action; detailed implementation procedures were not required. "Referenced" denotes the use of an outside framework or separate document. "Surface" indicates naming or acknowledging, but not deeply responding to, a relevant issue. A dash indicates no engagement. Foronda's (2008) attributes and Resnicow et al.'s (1999) depth of engagement informed the analysis.

Table 3
Engagement with specific cultural sensitivity dimensions across 28 universities with AI principles

University	Indigenous knowledges	Linguistic diversity/language support	Equity of access	Recognition of bias and discrimination
Monash	Substantive	—	Substantive	Substantive
New England	Substantive	—	Surface	Substantive
Charles Darwin	Substantive	—	Substantive	Substantive
Queensland	Substantive	—	Substantive	Substantive
Swinburne	Referenced	—	—	Substantive
Victoria	Surface	—	Surface	—
Bond	—	—	Substantive	Substantive
Deakin	—	—	Substantive	Substantive
UTS	—	—	—	Substantive
Melbourne	—	—	Substantive	Substantive
Macquarie	—	—	Substantive	Substantive
Western Sydney	—	—	Substantive	Surface
James Cook	—	—	Substantive	Surface
Charles Sturt	—	—	Surface	Surface
RMIT	—	—	Surface	Surface
UNSW	—	—	Surface	—
ACU	—	—	Surface	Surface
Canberra	—	—	—	—
Federation	—	—	Surface	Surface
La Trobe	—	—	Surface	Substantive
Newcastle	—	—	Substantive	—
Edith Cowan University	—	Surface	—	Substantive
Sydney	—	—	—	Surface
Adelaide	—	—	—	—
USC	—	—	—	—
ANU	—	—	—	—
Curtin	—	—	—	Surface
Southern Cross	—	—	—	—

Indigenous knowledges

As Table 3 shows, only four universities – Monash University, the University of New England, the University of Queensland and Charles Darwin University – acknowledge and highlight the importance of AI and Indigenous knowledges substantively. For instance, Monash states that large language models are built from materials written about, rather than by, Indigenous communities, and emphasises that AI tools "should not currently be used" when engaging with Indigenous knowledges, cultures or data. Similarly, the University of New England states that "Indigenous-led principles guide AI technology deployments," developed "in partnership with Aboriginal and Torres Strait Islander people." A lighter approach involves referencing external frameworks. The University of Queensland refers to the CARE Principles (Carroll et al., 2020) and the work of Worrell (2024), while Swinburne requires that AI use "comply with Swinburne's Indigenous Data Sovereignty Guidelines" without restating their content. Victoria University names "Protecting Country" as a relevant principle, but does not elaborate on it. By contrast, the remaining 22 universities make no reference to Indigenous knowledges in their AI principles.

Linguistic diversity and language support

None of the AI principles from the 28 universities analysed explicitly addresses the needs of students from non-English-speaking backgrounds. Language as a form of student learning is mentioned where Edith Cowan University lists "improving language learning" as a possible use of AI. By contrast, Bond University states that students must not use AI to translate their work into English as a way of undertaking authentic English learning. It is worth noting that this requirement from Bond represents a regulatory approach to language use, not a principle-level commitment to linguistic support. Also, universities that refer to Indigenous languages do so mainly in relation to cultural property and data governance. Monash, for instance, notes that "Indigenous languages, knowledges and cultural expressions" can be incorporated into datasets "without consent." However, such references are not connected to the needs of multilingual students, international students or students from non-English-speaking backgrounds.

Equity of access

As Table 3 shows, 18 of the 28 universities address equitable access, including 10 substantive and eight surface-level treatments. For example, the University of Melbourne was identified as substantive because it shows specific access barriers, such as financial disadvantage and disability, while Victoria University was at surface level because it refers broadly to equity and expanding opportunities without explaining what unequal access involves. However, these commitments are usually framed in relation to financial disadvantage, disability, location or unspecified forms of disadvantage, rather than cultural or linguistic difference. For instance, Melbourne refers to "financial disadvantage, disability, and other factors that disadvantage specific cohorts." Macquarie is committed to "eliminat[ing] barriers" so that AI tools can be "available regardless of financial or personal circumstances." Moreover, several universities use the broad language of access "regardless of background." For example, the Australian Catholic University promises support "for all students, regardless of background." Across these statements, terms such as "background" and "community" function as inclusive but underspecified terms. The cultural, linguistic, racial, Indigenous or migration-related meanings are not clearly defined, leaving cultural sensitivity present only as a broad equity aspiration rather than a culturally specific principle-level commitment.

Recognition of bias and discrimination

Lastly, 20 of the 28 universities address bias and discrimination in terms of AI use. These acknowledgements and references take two different forms. First, many universities frame bias and discrimination as a technical problem located in data, large language models or system outputs, and therefore as something to be removed and corrected. For example, La Trobe University refers to bias being "eliminated in AI datasets, hypotheses, and algorithms." Swinburne University requires users to check that AI "does not introduce bias" based on "gender, race, age, disability, or any other protected characteristic." Second, a smaller group of universities frame bias more structurally, linking it to wider social conditions and unequal institutional outcomes. Monash University, for instance, emphasises that it has taken steps to identify and reduce "undesirable biases in training data" in its AI systems. Most importantly, Deakin encourages stakeholders to consider "Who is

excluded or under-represented in the data or outputs?" and to recognise the "social, political and cultural biases inherent in AI."

In connection with bias, human-centredness appears frequently across the Australian universities' AI principles. Many are committed to keeping AI "human-centred," enhancing "human rights and dignity," preserving "human oversight" and ensuring that technology serves people rather than replaces them. However, this emphasis on "the human" is rarely accompanied by explications of humanness, including the cultural differences among the students and staff affected by advancing generative AI tools.

Discussion

The findings have major implications for theory and practice. The ensuing sections discuss those repercussions.

Surface engagement in addressing cultural sensitivity

As the findings show, cultural sensitivity operates at the level of stated value rather than embedded commitment in most universities' AI principles. This finding aligns with Resnicow et al.'s (1999) distinction between surface versus deep approaches to addressing cultural sensitivity. As universities' commitments to equity and fair access to AI are usually framed around financial disadvantage, disability, location, or general disadvantage – rather than cultural background – they assume homogeneity within a group (Resnicow et al., 1999). Hence, the engagement with cultural sensitivity in Australian universities' AI principles is generally insufficient and largely remains at a surface level. Viewed through Foronda's (2008) attributes, many principles demonstrate knowledge and consideration through commitments to equity, inclusion and fairness, but fewer progress towards the more developed forms of understanding, respect and tailoring evident when particular cultural groups or needs are explicitly addressed.

The problematic framing of bias and discrimination in AI principles further reinforces this pattern. Most Australian universities' treatment of bias as a technical problem risks reducing cultural sensitivity to system correction (of AI companies or third parties), instead of addressing how AI may (re)produce social, cultural and epistemic inequities. Only a few universities (such as Deakin and Queensland) have adopted a deeper framing. Generative AI is not culturally neutral, as it is trained on uneven datasets and shaped by dominant languages, knowledge systems and epistemologies (Herzog, 2025): an aspect of the technology that the universities are currently not addressing as well as they could.

Although most universities acknowledge differences and show a general respect for diverse backgrounds in their AI principles, they often lack consideration for specific cultural groups and fail to tailor practices to the needs of multilingual or international students. These cohorts are most exposed to AI biases (Liang et al., 2023; Wang et al., 2023). Exceptions like Monash University, which acknowledges the limitations of AI tools regarding Indigenous knowledges, demonstrate a deeper understanding of the technology. In other words, the sector's principles tend to emphasise knowledge and respect without moving towards tailoring for cultural sensitivity (Foronda, 2008).

Indigenous knowledges, cultural sensitivity and AI principles

A small group of universities engaging with Indigenous knowledges stand out from the others. Monash University's approach represents a form of deep-structure engagement largely absent elsewhere. Similarly, the University of New England's commitment to "Indigenous-led" governance and Charles Darwin's to community control of data both shift decision-making power to Indigenous communities themselves, in line with relevant Indigenous knowledge frameworks and principles (Carroll et al., 2020; Lodge et al., 2025). These examples demonstrate that deep engagement with cultural sensitivity in AI principles is approachable and functional.

Given Lodge et al.'s (2025) sector-wide framework that provides substantial scaffolding for cultural and linguistic equity, universities' AI principles' limited cultural sensitivity cannot be explained by an absence of national guidance. Rather, Australian universities appear to have only partially taken up the cultural and linguistic commitments outlined by Lodge et al. (2025). Based on this study's findings, a framework – captured visually in Figure 1 – is offered to help institutions and their staff move towards the development of more

robust, culturally sensitive AI principles. In the proposed framework, institutions move from the development of AI principles to the implementation of cultural sensitivity in those principles, and ultimately to the co-development of principles with diverse (and especially Indigenous) community members.

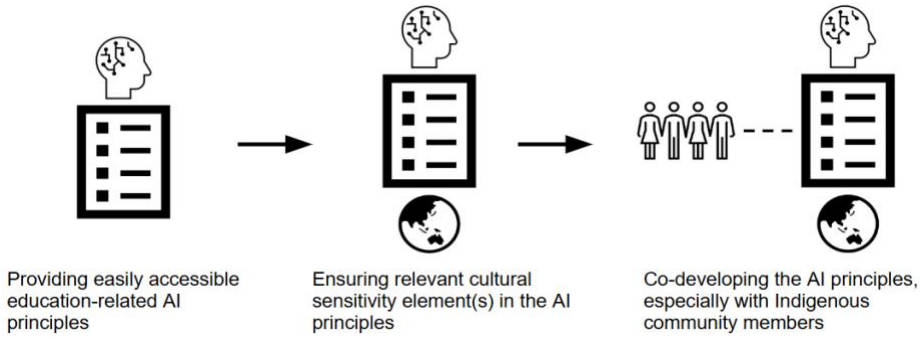


Figure 1. Culturally Sensitive AI Principles Progression Framework (author-developed image)

Specifically, the first stage of the Figure asks universities to provide easily accessible education-related AI principles. Table 1 identifies 14 universities with only operational guidance, login-restricted principles or no identifiable principles. Institutions can publish a clearly identified statement of their AI commitments and connect it to relevant policies. The second stage incorporates specific cultural commitments into AI principles. Tables 2 and 3 show the difference between generic values and developed engagement. Monash's restrictions on AI use involving Indigenous knowledges illustrate how a cultural risk can inform a specific institutional commitment. The third stage features the co-development of principles with diverse communities, especially Indigenous community members. The University of New England's commitment to Indigenous-led principles and Charles Darwin's recognition of community control over data provide documentary grounds for this third stage. Co-development also requires meaningful participation in setting priorities, permitted uses and review.

Implications and recommendations

The findings of this study carry both theoretical and practical implications. In terms of theory, this study extends the cultural sensitivity literature into the nascent domain of institutional AI governance. The research demonstrates that constructs such as surface and deep structure (Resnicow et al., 1999), as well as cultural sensitivity attributes (Foronda, 2008), can be used to examine AI-related policy. In terms of practice, the findings indicate the gaps in Australian universities' AI principles that can be addressed.

This study proposes several recommendations. First, universities should move beyond naming inclusion in general terms and specify what, exactly, inclusion requires in practice. This specification means translating broad commitments into concrete provisions that address multilingual writing practices, the limitations of AI detection for non-native English writers, and unequal access to paid AI tools, so that cultural sensitivity becomes operational rather than aspirational (Wang et al., 2023). Second, universities should engage more directly with the Indigenous data governance commitments already present in the Australian Framework (Lodge et al., 2025), including Indigenous data sovereignty and the CARE Principles (Carroll et al., 2020). Third, universities should explicitly name cultural sensitivity as a criterion for responsible AI use and connect it to the established literature. This step would help address the conceptual gap identified in the review and provide clearer guidance for institutional practice. Finally, crucially, universities should make their AI principles publicly accessible rather than login-restricted, so that their stated commitments to transparency are reflected in their own governance practices.

Conclusion

The development of culturally sensitive AI principles will only become more important given AI's continual growth and higher education's ongoing internationalisation. This study's findings have shown that cultural sensitivity in universities' AI principles can be strengthened significantly. The paper has argued that all universities not only need to provide robust, publicly accessible educational AI principles, but also actively integrate cultural sensitivity into these principles. It has offered a new approach – the Culturally Sensitive AI

Principles Progression framework – to facilitate this integration. The paper opens several further research avenues, some of which stem from its limitations. First, the paper examined the one case study; future research could examine other cases/countries. Second, publicly available documents were analysed; further studies could also seek to obtain and examine internal AI policy resources. Third, the data were textual and the coding was interpretive; future research could examine the implementation of AI principles in practice.

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