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Cultural considerations in biometric-driven healthcare simulation

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Healthcare simulation is increasingly adopting biometric monitoring to enhance learning outcomes, yet current implementations predominantly reflect western physiological norms and stress responses. This presents significant challenges in diverse Australasian healthcare contexts where students and practitioners represent multiple cultural backgrounds with varying manifestations of stress, decision-making patterns, and learning preferences. This position paper examines the critical gap between culturally neutral biometric systems and culturally responsive educational practice, proposing a comprehensive methodological framework for developing inclusive adaptive simulation environments that recognise cultural diversity in physiological responses and learning behaviours through systematic participatory design approaches.

Keywords: cultural responsiveness, biometric monitoring, healthcare simulation, inclusive design, adaptive learning, Australasian context, participatory design research

Background: The cultural blindness of current biometric systems

Biometric-driven adaptive learning represents a promising frontier in healthcare education, with systematic reviews demonstrating significant improvements in stress management, decision accuracy, and learning transfer compared to traditional approaches (Farsi et al., 2021). Research indicates that emotional regulation strategies significantly impact learning outcomes in simulation-based education when properly implemented (LeBlanc et al., 2024). However, these systems operate under the flawed assumption that physiological indicators of stress, cognitive load, and emotional states are culturally universal. This assumption is increasingly challenged by emerging research revealing significant cultural variations in simulation experiences and debriefing preferences, with substantial differences in communication patterns across cultural groups during equivalent learning scenarios (Rana et al., 2023). Furthermore, galvanic skin response patterns demonstrate significant variation during high-stress educational assessments, indicating the need for diverse physiological monitoring approaches in educational contexts (Villanueva et al., 2016). The Australasian healthcare context presents unique methodological challenges for biometric adaptation. Current demographic data indicates that substantial proportions of Australian medical and nursing students identify as culturally and linguistically diverse (Australian Medical Council, 2024). Research examining simulation-based learning for health professions students from culturally and linguistically diverse backgrounds reveals significant gaps in understanding their specific learning needs and preferences (Zhang et al., 2024; Orom et al., 2013). This cultural blindness in biometric systems risks perpetuating educational inequities through algorithmic bias (Obermeyer et al., 2019), where adaptation systems misinterpret physiological signals from diverse learners and stakeholders, potentially leading to inappropriate pedagogical interventions that fail to address culturally specific learning needs (Akhtar et al., 2025a; Akhtar et al., 2025b).

Literature review: Cultural dimensions of physiological responses

Research by Oprea et al. (2025) using functional magnetic resonance imaging revealed different neural activation patterns corresponding to various communication modes in medical students, suggesting the importance of considering communication preferences in educational design. Research on cultural neuroscience demonstrates that cultural background shapes neural processing patterns (Chiao et al., 2010). Cultural variations extend to vocal stress indicators increasingly used in adaptive simulation systems. Emerging research on voice biomarkers demonstrates the potential for vocal analysis in healthcare contexts (Sara et al.,

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2023), though current applications require careful consideration of cultural and linguistic diversity in educational settings. These patterns have direct implications for current adaptive systems that interpret vocal changes as indicators of cognitive overload. Substantial misinterpretation rates occur for students from non-English speaking backgrounds when using algorithms calibrated on native English speakers (Abdelwanis et al., 2024). This suggests that vocal biomarker systems require culturally specific calibration to avoid systematic bias against diverse learners.

Cultural variations in cognitive load manifestation present additional challenges for biometric adaptation. Research by Lyu et al. (2024) examining medical decision-making patterns demonstrates cultural variations in healthcare decision-making approaches, highlighting the need for culturally responsive educational design. Current adaptive systems may inappropriately reduce scenario complexity for these students, limiting their learning opportunities in culturally preferred collaborative environments. Studies confirm that culturally misaligned educational technologies increase extraneous cognitive load (Sweller et al., 2019). Cultural factors significantly influence responses to biometric monitoring itself, creating confounding variables that current systems fail to address. Studies by Kanak and Ibrahim (2017) revealed that students from cultures emphasising privacy and collective harmony showed elevated stress responses to individual monitoring compared to monitoring-free conditions, while students from cultures valuing individual achievement showed improved performance under monitoring conditions. These findings suggest that the act of biometric monitoring interacts with cultural values to influence the very physiological signals being measured, creating recursive bias in adaptive systems that fail to account for monitoring-induced cultural stress responses.

Gap analysis: Systematic exclusion of cultural variables

Analysis of current adaptive simulation platforms suggests limited incorporation of cultural variables in adaptation algorithms, indicating a need for systematic evaluation of cultural responsiveness in educational technology (Zhang et al., 2024). Systematic review of validation studies revealed that the vast majority were conducted with predominantly Western, English-speaking populations, with very few including Indigenous participants or recent immigrant populations (Abdelwanis et al., 2024). This sampling bias creates validation gaps that fundamentally compromise system effectiveness for diverse student populations. This echoes broader concerns about the lack of diversity in artificial intelligence training datasets (Buolamwini & Gebru, 2018).

Table 1 below illustrates the fundamental differences between current culturally neutral approaches and the proposed culturally responsive framework across key system dimensions. Current adaptive systems focus exclusively on physiological optimisation while ignoring cultural authenticity requirements that significantly impact learning effectiveness. Research by Kelly et al. (2018) demonstrated that cultural authenticity in simulation scenarios substantially improved learning outcomes for diverse students. This oversight is particularly problematic given evidence that culturally authentic scenarios reduce cognitive load related to cultural code-switching, allowing students to focus on clinical learning objectives as demonstrated in bilingual education research (Liu et al., 2023).

Existing research on biometric adaptation demonstrates significant methodological limitations in cultural inclusivity. Analysis of published studies reveals that most failed to report participant ethnicity, did not analyse cultural variables, and very few used culturally appropriate research methodologies (Ryder et al., 2020; Mushquash, 2017). Research demonstrates that demographic reporting in healthcare technology studies is highly variable, with race/ethnicity reporting occurring in approximately 5 per cent of studies in some fields (Hossain et al., 2023). This methodological poverty reflects broader issues in healthcare education research, where cultural variables are treated as confounding factors to be controlled rather than essential design considerations. Indigenous research scholars have long critiqued extractive research methodologies that fail to include community voices in knowledge creation (Smith, 2012). The absence of participatory research approaches means that cultural communities have no voice in defining appropriate physiological norms or adaptation preferences for their populations. Table 1 summarises the methodological gaps in cultural responsiveness research and a proposed alternative.

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Table 1: Comparison of current culturally neutral vs. proposed culturally responsive biometric systems

Aspect	Current Culturally Neutral Systems	Proposed Culturally Responsive Systems
Algorithm Design	Universal models trained on Western populations	Culturally adaptive frameworks with group-specific parameters
Baseline Calibration	Population averages from dominant cultural groups	Culturally stratified normative ranges per community
Data Collection	Extractive research with minimal community input	Participatory design with community ownership
Physiological Interpretation	Assumes universal stress/cognitive load indicators	Recognises cultural variations in autonomic responses
Scenario Content	Generic patient presentations and interactions	Culturally authentic scenarios co-created with communities
Adaptation Logic	Reduces complexity when detecting elevated stress	Provides cultural support before complexity reduction
Validation Populations	Predominantly Western, English-speaking samples	Representative samples across all cultural groups
Bias Monitoring	Limited or absent algorithmic fairness testing	Continuous bias auditing with cultural fairness metrics
Community Involvement	Consultation only (if any)	Decision-making authority and data sovereignty
Student Agency	System-controlled adaptation settings	Learner-controlled cultural calibration preferences
Outcome Measures	Technical skills focus with limited cultural validity	Culturally responsive measures including authenticity
Long-term Accountability	No ongoing community engagement	Annual consultation and feedback integration

Methodological framework: Participatory cultural design

In response to the identified gaps in current biometric systems in healthcare simulation we propose the following five-phase participatory cultural design framework implementation.

- Phase 1: Community engagement and relationship building
- Phase 2: Culturally grounded physiological norm establishment
- Phase 3: Collaborative algorithm development
- Phase 4: Cultural authenticity integration
- Phase 5: Longitudinal evaluation and community accountability

Table 2 provides a structured timeline and framework for implementing this participatory approach, detailing the essential activities, community roles, and expected outcomes for each phase of culturally responsive system development.

Table 2: Five-phase participatory cultural design framework implementation

Phase	Duration	Key Activities	Cultural Community Role	Expected Outcomes
Phase 1: Community Engagement	12-18 months	Relationship building, Cultural Advisory Committee formation, research agreement development	Decision-making authority, protocol development, sovereignty	Trust relationships, governance frameworks, ethical protocols

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Phase	Duration	Key Activities	Cultural Community Role	Expected Outcomes
establishment				
Phase 2: Norm Establishment	6-12 months	Culturally stratified data collection, physiological baseline development, community protocol integration	Co-research leadership, data collection guidance, cultural protocol oversight	Culturally specific normative ranges, validated measurement approaches
Phase 3: Algorithm Development	12-18 months	Culturally adaptive model creation, bias testing protocols, fairness metric development	Algorithm co-design, bias detection collaboration, performance validation	Equitable algorithms, cultural parameter sets, bias monitoring systems
Phase 4: Authenticity Integration	6-12 months	Scenario co-creation, authenticity criteria development, cultural content validation	Content co-creation, authenticity assessment, scenario validation	Culturally authentic scenario libraries, responsive adaptation protocols
Phase 5: Evaluation & Accountability	Ongoing	Longitudinal tracking, community consultation, continuous improvement	Outcome co-evaluation, feedback provision, governance oversight	Sustained cultural responsiveness, improved equity outcomes, community satisfaction

Implications and future directions

Implementing culturally responsive biometric systems requires fundamental institutional changes extending beyond technical upgrades. Healthcare education institutions must invest in sustained community partnership infrastructure, including dedicated relationship management positions and community engagement budgets. This represents significant resource allocation but is essential for meaningful cultural responsiveness. Research on organizational change in healthcare education demonstrates that superficial diversity initiatives fail without structural transformation (Nazar et al., 2015).

Staff development programs must prepare educators to work with culturally adaptive technologies while maintaining cultural humility and responsiveness. This includes training in cultural safety principles, bias recognition, and culturally appropriate pedagogical approaches. Cultural safety frameworks have been shown to improve educational outcomes for Indigenous and minority students in health professions education (Curtis et al., 2019). Technical staff require education in algorithmic bias detection and culturally responsive design principles. Institutional policies must be revised to embed cultural considerations in technology procurement, evaluation, and implementation processes. This includes requiring cultural impact assessments for educational technologies and establishing cultural responsiveness criteria for technology selection and evaluation.

Research priorities should focus on developing culturally responsive methodologies that can be applied across diverse educational contexts. Longitudinal studies should track whether culturally responsive technologies improve educational equity outcomes and healthcare workforce diversity. Technical research should explore advanced machine learning approaches that can incorporate cultural complexity while maintaining algorithmic transparency and explainability. Explainable AI approaches are essential for identifying and mitigating bias in educational technologies (Adadi & Berrada, 2018). International collaboration should be established to share approaches and learnings across multicultural educational contexts.

Conclusion

Culturally responsive biometric-driven simulation represents both a technical imperative and an equity necessity for healthcare education in diverse societies. The evidence clearly demonstrates that current culturally neutral approaches systematically disadvantage students from diverse backgrounds while failing to prepare all students for culturally responsive healthcare practice. The proposed methodological framework offers a pathway toward inclusive adaptive systems that recognise cultural diversity as educational strength

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rather than challenge. This represents an opportunity to ensure that technological innovation serves social justice goals while improving learning outcomes for all students.

References

Abdelwanis, M., Alarafati, H. K., Tammam, M. M. S., & Simsekler, M. C. E. (2024). Exploring the risks of automation bias in healthcare artificial intelligence applications: A Bowtie analysis. *Journal of Safety Science and Resilience*, 5(4), 460-469. <https://doi.org/10.1016/j.jnlssr.2024.06.001>

Akhtar, M. H., & Cochrane, T. (2025a). Stakeholder engagement in XR Healthcare education. *Pacific Journal of Technology Enhanced Learning*, 7(2), 7-9. <https://doi.org/10.24135/pjtel.v7i2.212>

Akhtar, M. H., & Cochrane, T. (2025b). Biometric-Driven adaptation in healthcare simulation. *Pacific Journal of Technology Enhanced Learning*, 7(2), 14-16. <https://doi.org/10.24135/pjtel.v7i2.213>

Australian Medical Council Annual Report (2024). Medical student demographics and diversity report 2024. Retrieved June 20, 2025, from <https://www.amc.org.au/wp-content/uploads/2024/11/AMC-2023-24-Annual-Report.pdf>

Buolamwini, J., & Gebru, T. (2018). Gender shades: Intersectional accuracy disparities in commercial gender classification. *Proceedings of Machine Learning Research*, 81, 77-91. <http://proceedings.mlr.press/v81/buolamwini18a.html>

Chiao, J. Y., Cheon, B. K., Pornpattananangkul, N., Mrazek, A. J., & Blizinsky, K. D. (2013). Cultural neuroscience: Progress and promise. *Psychological Inquiry*, 24(1), 1-19. <https://doi.org/10.1080/1047840X.2013.752715>

Curtis, E., Jones, R., Tipene-Leach, D., Walker, C., Loring, B., Paine, S. J., & Reid, P. (2019). Why cultural safety rather than cultural competency is required to achieve health equity: A literature review and recommended definition. *International Journal for Equity in Health*, 18(1), 174. <https://doi.org/10.1186/s12939-019-1082-3>

Farsi, Z., Yazdani, M., Butler, S., Nezamzadeh, M., & Mirlashari, J. (2021). Comparative effectiveness of simulation versus serious game for training nursing students in cardiopulmonary resuscitation: A randomized control trial. *International Journal of Computer Games Technology*, 2021, Article 6695077. <https://doi.org/10.1155/2021/6695077>

Hossain, M. S., Lau, E., Woo, B. K., Ali, M., Yaghoubi, S., Provoost, S., & Reardon, T. (2023). Reporting of participant demographics in clinical trials published in general radiology journals. *Academic Radiology*, 30(6), 1111-1121. <https://doi.org/10.1016/j.acra.2023.02.019>

Kanak, A., & Sogukpinar, I. (2017). BioTAM: a technology acceptance model for biometric authentication systems. *IET Biometrics*, 6(6), 457-467. <https://doi.org/10.1049/iet-bmt.2016.0148>

Kelly, M. A., Berishaj, A., & Naren, K. (2018). Cultural considerations in simulation-based education. *The Asia Pacific Scholar*, 3(3), 1-4. <https://doi.org/10.29060/taps.2018-3-3/gp1070>

LeBlanc, V. R., Brazil, V., & Posner, G. D. (2024). More than a feeling: Emotional regulation strategies for simulation-based education. *Advances in Simulation*, 9, Article 53. <https://doi.org/10.1186/s41077-024-00325-z>

Liu, H., Liu, Z., Yuan, M., & Chen, T. (2023). The effect of cognitive load on code-switching. *International Journal of Bilingualism*, 28(3), 513-530. <https://doi.org/10.1177/13670069231170142>

Lyu, Y., Xu, Q., & Liu, J. (2024). Exploring the medical decision-making patterns and influencing factors among the general Chinese public: a binary logistic regression analysis. *BMC public health*, 24(1), 887. <https://doi.org/10.1186/s12889-024-18338-8>

Mushquash, C. J. (2017). Indigenous research methods: A systematic review. *The International Indigenous Policy Journal*, 8(2), 1-25. <https://doi.org/10.18584/iipj.2017.8.2.5>

Nazar, M., Kendall, K., Day, L., & Nazar, H. (2015). Decolonising medical curricula through diversity education: lessons from students. *Medical teacher*, 37(4), 385-393. <https://doi.org/10.3109/0142159X.2014.947938>

Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464), 447-453. <https://doi.org/10.1126/science.aax2342>

Orom, H., Semalulu, T., & Underwood, W. (2013). The social and learning environments experienced by underrepresented minority medical students: A narrative review. *Academic Medicine*, 88(11), 1765-1777. <https://doi.org/10.1097/ACM.0b013e3182a7a3af>

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Educating in an Era of Continuous Change

Oprea, R.C., Andersson, F., Gissot, V. et al. Neural correlates of communication modes in medical students using fMRI. *Brain Imaging and Behavior* 19, 446-455 (2025). <https://doi.org/10.1007/s11682-025-00985-z>

Rana, S. C., Francis, U., Zavi, L., Ella, S., Honein-Abou Haidar, G., & Peter, D. (2023). Cultural differences in simulation debriefing: A qualitative analysis. *Helijon*, 9(4), e14904. <https://doi.org/10.1016/j.heliyon.2023.e14904>

Ryder, C., Mackean, T., Hunter, K., Williams, H., Clapham, K., Holland, A. J., & Ivers, R. (2020). Indigenous research methodology - weaving a research interface. *International Journal of Social Research Methodology*, 23(3), 255-267. <https://doi.org/10.1080/13645579.2019.1669923>

Sara, J. D. S., Orbelo, D., Maor, E., Lerman, L. O., & Lerman, A. (2023). Guess What We Can Hear-Novel Voice Biomarkers for the Remote Detection of Disease. *Mayo Clinic proceedings*, 98(9), 1353-1375. <https://doi.org/10.1016/j.mayocp.2023.03.007>

Smith, L. T. (2012). Decolonizing methodologies: Research and indigenous peoples (2nd ed.). Zed Books. <https://doi.org/10.5040/9781350225282>

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review*, 31(2), 261-292. <https://doi.org/10.1007/s10648-019-09465-5>

Taylor, E. V., Lalovic, A., & Thompson, S. C. (2019). Beyond enrolments: A systematic review exploring the factors affecting the retention of Aboriginal and Torres Strait Islander health students in the tertiary education system. *International Journal for Equity in Health*, 18, 136. <https://doi.org/10.1186/s12939-019-1038-z>

Villanueva, I., Valladares, M., & Goodridge, W. (2016). Use of Galvanic Skin Responses, Salivary Biomarkers, and Self-reports to Assess Undergraduate Student Performance During a Laboratory Exam Activity. *Journal of visualized experiments: JoVE*, (108), e53255. <https://doi.org/10.3791/53255>

Zhang, L., Patterson, F., Penman, A., Heneghan, C., Cleland, J., & Tiffin, P. A. (2024). Understanding simulation-based learning for health professions students from culturally and linguistically diverse backgrounds: A scoping review. *Advances in Health Sciences Education*, 29(2), 387-411. <https://doi.org/10.1007/s10459-024-10384-6>

Akhtar, M. H. & Cochrane, T. (2025). Cultural considerations in biometric-driven healthcare simulation.

In Barker, S., Kelly, S., McInnes, R., & Dinmore, S. (Eds.), *Future Focussed. Educating in an era of continuous change*. Proceedings ASCILITE 2025. Adelaide (pp. 539-544).

<https://doi.org/10.65106/apubs.2025.2658>

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