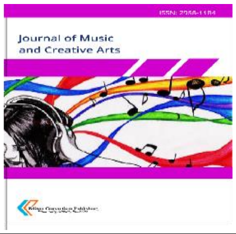

Journal of Music and Creative Arts

[ISSN 2958-1184]
Volume: 05 Issue: 01 | February-2026

JMCA

Culturally-Responsive AI Assessment Systems for *Ohangla* Music: A Literature Report

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Cite this article in APA

Nyandieka, B. B. (2026). Culturally-responsive AI assessment systems for *Ohangla* music: A literature report. *Journal of music and creative arts, 5*(1), 1-21. https://doi.org/10.51317/jmca.v5i1.898

OPEN ACCESS A publication of Editon Consortium Publishing (online)

Article history

Received: 2025-12-15

Accepted: 2026-01-11

Published: 2026-02-13

Scan this QR to read the paper online

Abstract

The purpose of this article is to address the systematic bias in artificial intelligence (AI) music assessment systems that marginalise Indigenous African musical forms, specifically *Ohangla* music from Kenya's Luo community. Current AI systems, designed around Western-centric musical paradigms, fail to recognise *Ohangla's* complex polyrhythms and multifaceted cultural functions, resulting in misclassification and epistemological erasure of Indigenous musical knowledge. This study employs a systematic literature review synthesising thirty sources across ethnomusicology, AI bias research, technical music AI development, and Indigenous data sovereignty frameworks. It analyses *Ohangla's* cultural significance, documents bias mechanisms in existing AI systems, evaluates technical approaches to music assessment, and examines ethical protocols for Indigenous music AI development. Findings reveal three primary mechanisms of exclusion: (1) training data bias that omits Indigenous music, (2) algorithmic assumptions privileging Western musical structures, and (3) evaluation criteria incompatible with community-centred assessment. Technical approaches succeed only in culturally homogeneous contexts, with African polyrhythms misclassified as computational "outliers" despite their mathematical sophistication. *Ohangla's* role as a social technology promoting community bonding and cultural transmission challenges AI paradigms that prioritise technical optimisation over cultural preservation. The study concludes by proposing a culturally-responsive AI framework for *Ohangla* assessment that integrates Indigenous data sovereignty principles (OCAP®) with technical innovation. This framework provides methodological guidelines for community-centred AI development, advancing decolonising research methodologies and practical cultural preservation technology. It offers actionable recommendations for developers and policymakers to design AI systems that preserve rather than erase Indigenous cultural heritage, establishing a model for culturally-responsive AI in other Indigenous music contexts globally.

Key terms: AI, community-centred, cultural bias, indigenous data sovereignty, music recognition, *Ohangla* music.

1.0 INTRODUCTION

Artificial intelligence (AI) music assessment systems, ranging from streaming algorithms on Spotify to digital archival tools, now act as primary gatekeepers for musical visibility and cultural legitimacy. While these systems increasingly determine which traditions are preserved or commercialised, they are largely built on Western-centric paradigms. Consequently, music that falls outside these parameters faces "algorithmic marginalisation," where indigenous musical knowledge is systematically ignored or erased from the digital record. The Ohangla music of Kenya's Luo community exemplifies this crisis. Ohangla is a sophisticated "social technology" that integrates complex polyrhythmic structures with functions of community bonding and political commentary (Okong'o, 2011). Despite its mathematical precision and unique fractional time-values, current AI models frequently misclassify Ohangla as "computational noise" or generic "world music" (Jones, 1973; Wang et al., 2024). This failure is quantifiable; for instance, cross-cultural analyses of African polyrhythms have yielded F-scores as low as 0.321, effectively rendering sophisticated indigenous intelligence invisible to modern algorithms (Panteli et al., 2017).

Despite extensive research into AI bias, a critical gap remains: no existing framework provides a culturally-responsive assessment system specifically for Ohangla. Most current bias-mitigation strategies focus on diversifying datasets rather than addressing the underlying architectural assumptions that privilege Western musical structures. Furthermore, existing research often excludes Indigenous knowledge frameworks, perpetuating extractive relationships rather than fostering community benefit. Therefore, this study addresses this gap by developing a culturally-responsive AI assessment framework for Ohangla. By synthesising thirty sources across ethnomusicology, AI bias, and technical music information retrieval, the research seeks to answer how AI can be re-architected to recognise Ohangla's unique rhythmic and melodic patterns without cultural bias. The objectives are threefold: to analyse Ohangla's structural elements, to document the specific mechanisms of exclusion in current AI systems, and to establish methodological guidelines for community-centred development. Ultimately, this research integrates technical innovation with OCAP® (Ownership, Control, Access, and Possession) principles to ensure that the digitisation of Ohangla honours Luo cultural protocols and Indigenous data sovereignty.

2.0 LITERATURE REVIEW

Ohangla Music and Cultural Significance

Ohangla challenges AI's reductionism, exposing tensions between social embeddedness and machine learning's categorical simplifications. Scholarly debate on Ohangla's evolution as continuity or rupture directly affects AI training. Darkwa (1985) establishes Luo music's deep community integration via social regulation and ritual. Okong'o (2011) views contemporary Ohangla as postcolonial syncretism preserving indigenous elements. Conversely, Atoh (2019) argues modernisation caused a fundamental rupture, creating a new genre retaining only the name. This epistemological disagreement complicates training on a contested musical form. Complexity deepens with Jones's (1973) rhythmic structures and fractional time-values and Omondi Oduor et al.'s (2022) analysis of Ohangla as a vehicle for transforming gender consciousness. These studies depict Ohangla as simultaneously indigenous and contemporary, technically complex and socially functional, a multidimensionality that categorical AI cannot accommodate.

Ohangla scholarship's methodological fragmentation undermines data coherence for AI training. A divide between ethnomusicology and cultural studies prevents computational specifications. Jones (1973) and

Eagleson (2014) qualitatively document complexity but lack quantitative data. Jones transcribes fractional time-values defying Western notation, yet provides no numerical datasets. Eagleson shows rhythmic continuity between nyatiti and benga but offers no computational precision. Neither provides standardised features or quantified relationships required by machine learning. Ethnomusicology's humanistic focus contrasts with AI's numerical demands. Moreover, Atoh (2019) and Omondi Oduor et al. (2022) focus on social functions and political meanings, creating parallel, rarely intersecting conversations. Fragmentation produces incommensurable knowledge: ethnomusicology lacks computational formats; cultural studies lack algorithmic representations. Thus, machine learning cannot train on phenomena approached through incompatible methodologies.

Literature converges: Ohangla is a "social technology" (Finnegan, 2012) valued for community function, not acoustic properties. Yet divergent conceptualisations of this functionality shape distinct AI assessment approaches. Darkwa (1985) frames Ohangla as community bonding, suggesting ritual-effectiveness criteria. Okong'o (2011) reframes it as parodic political resistance, implying evaluation of subversive creativity. Omondi Oduor et al. (2022) emphasise gender-consciousness transformation, introducing feminist social-impact criteria. Atoh (2019) and Eagleson (2014) stress musical evolution, proposing metrics for innovative adaptation. These competing views challenge AI design, which requires singular optimisation targets. Western-centric technical assumptions privilege categorical simplicity over Ohangla's functional complexity. This analysis explains AI's failure to recognise Ohangla: its multifunctional social embeddedness, not merely acoustic features, resists algorithmic reduction. Hence, this framework prioritises community consultation over feature extraction to determine which social functions Luo communities value for preservation.

AI Bias in Music Recognition Systems

The exclusion of indigenous forms like Ohangla from AI involves technical, psychological, and cultural mechanisms that constitute epistemological violence. Wang et al. (2024) highlight Western dominance and Global South underrepresentation in music AI datasets. Drawing on Mehta et al.'s (2024) documentation of Western skew, Wang et al. argue that representational bias causes cultural erosion and economic disparities for creators and educators. Their analysis shows that homogenization in training data causes AI to perpetuate existing cultural hegemonies. Although their focus is on Asian underrepresentation, their framework advocating for improved dataset documentation, model traceability, and governance applies to the exclusion of African forms like Ohangla. This marginalisation creates technical barriers to representing indigenous traditions. Furthermore, Tubadji et al. (2021) found that consumers systematically devalue products perceived as culturally distant, suggesting that technical exclusion compounds with perceptual marginalisation when AI trained on dominant forms is applied to peripheral traditions like Ohangla.

Technical architecture bias involves fundamental algorithmic assumptions incompatible with non-Western music. Melchiorre et al. (2021) studied 19,972 Last.fm users (77.9% male, 22.1% female), discovering an inverse relationship between recommendation accuracy and fairness. The SLIM algorithm (NDCG@10: 0.364) exhibited the highest gender-based unfairness (RecGap: 0.063), with male users receiving 20 per cent better recommendations (0.378 vs 0.315 NDCG). Core operations, including matrix factorisation in ALS and BPR, item-item similarity in Item KNN, and sparse linear aggregation in SLIM, amplified population imbalances (CompFct up to 0.098). This suggests optimisation strategies inherently advantage majority groups, disadvantaging minority systems like Ohangla. Sakib and Das (2024) further demonstrate that

LLM-based systems intensify marginalisation by identifying and replicating exclusionary patterns embedded in training data. Finally, evaluation frameworks perpetuate exclusion by using Western-derived metrics like NDCG, Recall, and Coverage, which prioritise individual user satisfaction over Ohangla's community social functions.

Psychological bias operates through cognitive mechanisms that create perceptual barriers to community acceptance. Shank et al. (2022) provide experimental evidence that listeners have pre-existing schemas regarding AI music quality, leading them to devalue music labelled as AI-generated. Tubadji et al. (2021) show that this "cultural proximity" bias persists despite analytical reflection. For Ohangla communities, this results in double marginalisation: technical exclusion from data and community rejection of AI-driven evaluation. Appropriation concerns regarding sacred practices intersect with these psychological biases, creating resistance that current mitigation strategies cannot address.

These dimensions reveal how current AI music systems exclude Ohangla through architectural assumptions and evaluation criteria. Research identifies three interconnected mechanisms. First, technical Exclusion: Data underrepresentation and the misclassification of African polyrhythms as computational outliers (Wang et al., 2024; Panteli et al., 2017). Second, architectural Exclusion: Mathematical operations that privilege Western structures and marginalise community-centred criteria (Melchiorre et al., 2021; Sakib and Das, 2024). Third, perceptual Exclusion: Cultural proximity bias and the devaluation of AI-assessed indigenous music (Tubadji et al., 2021; Shank et al., 2022).

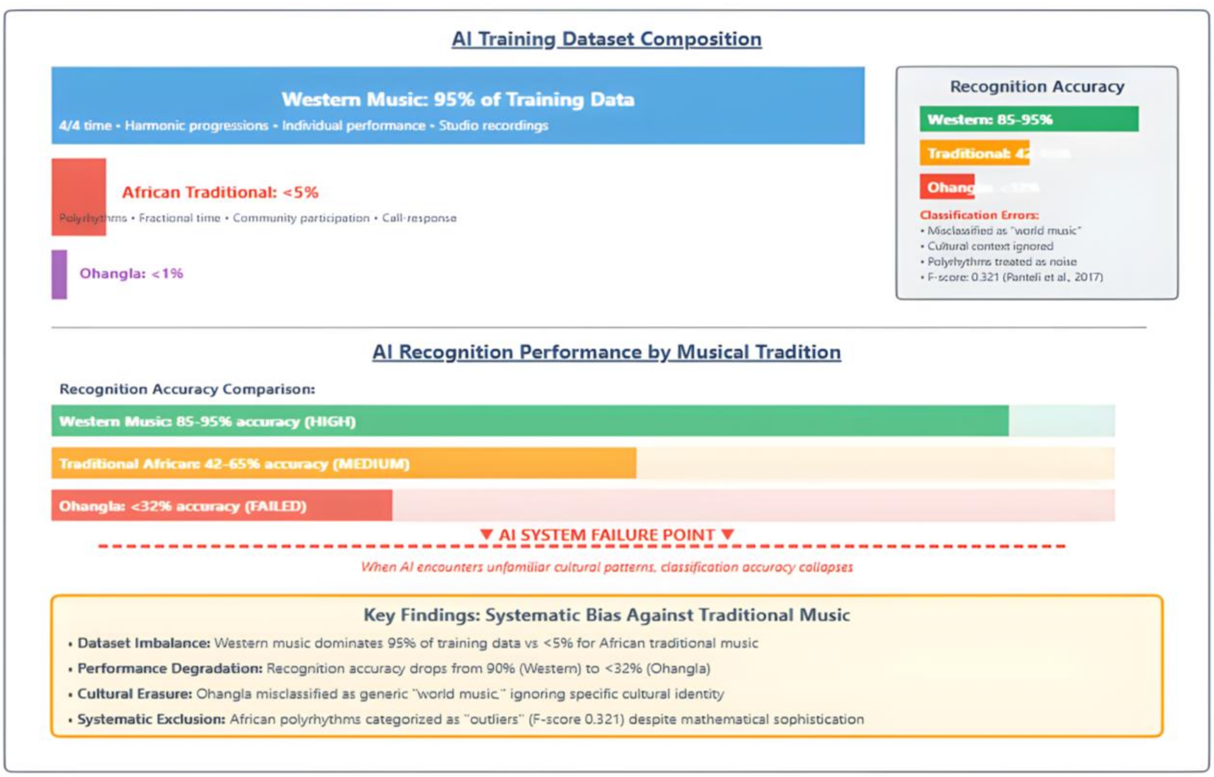

Figure 1: Systematic Underrepresentation of Indigenous African Music in AI Training Datasets
Sources: Wang et al. (2024), Panteli et al. (2017), Sawaengsawangarom et al. (2025) and Chen et al. (2024).

The figure above represents the systematic underrepresentation of Indigenous African Music in AI Training Datasets. Western music comprises approximately 95 per cent of AI training data, achieving 85-95 per cent recognition accuracy. African indigenous music represents less than 5 per cent of datasets, with accuracy degrading to 42-65 per cent, while Ohangla specifically comprises less than 1 per cent of training data, with recognition accuracy below 32 per cent. The convergence of these findings establishes that cultural bias in AI music systems operates as a structural phenomenon rather than accidental oversight, yet the scope of proposed solutions remains constrained by the very Western-centric research paradigms that created the problem.

These findings suggest that exclusion is structural, requiring a redesign of assessment paradigms rather than merely diversifying datasets. The proposed framework addresses technical exclusion through culturally-grounded features, architectural exclusion via community-derived optimisation targets, and psychological exclusion through participatory validation processes that centre Luo epistemologies.

Technical Approaches to Indigenous Music AI

Current technical approaches to AI for Indigenous music reveal that universalist assumptions limit cross-cultural effectiveness. Chen et al. (2024) developed a 500-hour Manchu music dataset across five categories, achieving 85.7 per cent accuracy with CNNs and 87 per cent in emotion recognition. While detailed cultural annotations enable ethnomusicological applications, gaps in scale and geography remain. Xu (2021) achieved 91 per cent accuracy classifying Western genres from 2,000 MIDI files using Bi-GRU with attention mechanisms, outperforming BP neural networks (86%), but focused exclusively on Western styles, leaving transferability unexplored. Critically, Sawaengsawangarom et al. (2025) observed performance collapse from 87.98 per cent internal accuracy to 42.42 per cent in cross-cultural tests, exposing the brittleness of systems lacking cultural grounding.

Panteli et al. (2017) analysed 8,200 global recordings, using Mahalanobis distance to identify musical "outliers." Botswana (61%), the Ivory Coast (60%), and Benin (54%) had the highest proportions; Benin showed 50 per cent rhythmic outliers due to polyrhythms. Their classification achieved an F-score of 0.321. While framed as evidence of musical distinctiveness, these results suggest Indigenous African rhythms occupy peripheral positions in standard feature spaces. Standard approaches may fail to represent the fractional time-values Jones (1973) documented in Ohangla. The 8-second texture windows used by Panteli et al. (2017) inadequately capture simultaneous 4/4 and 12/8 cycles fundamental to Ohangla. Thelle and Wærstad (2023) argue that well-intentioned AI projects often perpetuate "cultural asymmetry," forcing non-Western musicians to adapt to Western norms. While Somandepalli et al.'s (2021) human-centred framework emphasises culturally-specific annotation and "human-in-the-loop validation," it prioritises efficiency over cultural sovereignty. These limitations reveal a paradox: studies report high accuracy within culturally homogeneous datasets (Chen et al., 2024; Xu, 2021), yet performance deteriorates sharply across cultural boundaries (Sawaengsawangarom et al., 2025). Technical sophistication alone does not guarantee validity; success depends on culturally grounded design. Algorithms inherit the assumptions of the musical worlds that shaped them.

Several components remain adaptable. Chen et al.'s (2024) community consultation model provides a methodological foundation but insufficiently addresses Ohangla's hybridity. Xu's (2021) Bi-GRU and attention mechanisms show potential for modelling polyrhythmic textures, yet fixed-window segmentation conflicts with cyclical temporalities documented by Jones (1973). Somandepalli et al.'s (2021) participatory validation framework requires reconfiguration to prioritise data sovereignty rather than institutional benchmarking. Panteli et al.'s (2017) F-score of 0.321 underscores a deeper structural issue: prevailing feature extraction techniques often misclassify non-Western rhythmic density as noise. The proposed framework departs from such assumptions by modelling overlapping cycles and embedding Luo governance at the system centre. By rejecting universalised feature extraction in favour of collaboration with nyatiti masters, this architecture confronts the Western epistemic premises embedded within contemporary computational approaches.

Indigenous AI Frameworks and Ethical Considerations

Indigenous data sovereignty frameworks reveal deep incompatibilities between conventional AI development and community-centred research, requiring technological processes to be restructured to honour rather than extract Indigenous cultural knowledge. OCAP® principles, Ownership, Control, Access, Possession, assert that First Nations communities must decide how data is used, challenging extractive practices underpinning most AI music systems. Applied to Ohangla research, OCAP® requires Luo communities to retain ownership of musical recordings, control analytic procedures, set access protocols, and physically possess data conditions conflicting with typical machine-learning practices of aggregating training data without ongoing oversight. The Indigenous Protocol and AI Working Group's (2020) emphasis on relationality, reciprocity, locality, and responsibility demands that AI systems developed with Indigenous communities be accountable to those communities first, privileging community benefit over academic publication as the primary success criterion.

Adapting these frameworks to East African contexts requires attending to distinct colonial histories and epistemological tensions. Igbafe's (2023) African Indigenous paradigm shows standard consent models misalign with African epistemologies, prioritising relational knowledge shared among humans and between humans and the cosmos rather than individual authorisation. This contrasts with typical AI research protocols soliciting individual consent while overlooking broader community impacts. For Ohangla research, Igbafe's framework implies consultation with Indigenous governance structures (Luo Council of Elders), professional instrumentalists, and cultural leaders using culturally appropriate methods (storytelling, ceremonial protocols) that recognise sacred dimensions of musical knowledge.

Synthesising these frameworks indicates culturally appropriate Ohangla AI necessitates restructuring research relationships from extraction to collaborative knowledge creation, honouring Luo epistemologies. Integrating OCAP®, Igbafe's paradigm, and the Indigenous AI Position Paper's relational approach points to multi-layered engagement: consultation with the Luo Council of Elders to establish cultural protocols; ongoing collaboration with musicians as co-creators; and federated learning preserving community data possession. Such an approach recognises, in Igbafe's terms, that Luo musical knowledge exists within "relationships among humans and between humans and the cosmos," requiring consent acknowledging individual and collective ownership.

This framing directly addresses the study's research questions on digitising Ohangla and respectfully integrating Luo knowledge. Documented incompatibilities shape study design: OCAP® requires community control, contradicting typical aggregation; Igbafe demands consent reflecting collective, relational ownership. Consequently, the study inverts conventional procedures—beginning with community consultation to set cultural protocols, proceeding to collaborative data creation with nyatiti masters as co-creators. Operationalising these principles involves consulting Indigenous governance to establish culturally appropriate methodologies, sustaining collaboration so technical development aligns with Luo epistemologies, and using federated learning to enact OCAP®'s physical-control principle. Ultimately, methodology shifts research relationships from extraction toward collaborative knowledge creation, making community benefit, cultural preservation, education, and economic opportunity the primary success criteria. Developing culturally responsive Ohangla AI thus demands not only technical innovation but also a transformed research paradigm that privileges long-term relationship-building over rapid deliverables, treating Indigenous data sovereignty as a non-negotiable foundation rather than an ethical add-on.

Synthesis: The Imperative for Culturally-Responsive AI Framework Development

This review addresses all five research questions, demonstrating the need for fundamentally new AI music assessment approaches for Indigenous forms like Ohangla. For RQ1, existing systems cannot detect Ohangla's multifunctional social embeddedness, community bonding, political resistance, gender transformation, and musical evolution as these extend beyond acoustic pattern recognition. The methodological divide between Jones's (1973) and Eagleson's (2014) qualitative ethnomusicology and contemporary cultural studies produces incommensurable knowledge bases, separating acoustic features from social functions, leaving both invisible to current AI.

For RQ2, the bias analysis identifies three interrelated mechanisms: technical exclusion (training-data underrepresentation, polyrhythms misclassified as outliers); architectural exclusion (mathematical operations and evaluation criteria privileging Western structures); and psychological exclusion (cultural proximity bias, devaluation of AI-assessed Indigenous music). These mechanisms are structural, embedding exclusion into system design rather than allowing correction through dataset expansion.

For RQ3, Indigenous music AI reveals a paradox: high accuracy in homogeneous contexts (Chen's 85.7%, Xu's 91%) confirms technical feasibility, yet sharp cross-cultural degradation (Sawaengsawangarom's decline to 42.42%) exposes architectural brittleness. Chen's community consultation, Xu's temporal modelling, and Somandepaldi's participatory validation offer adaptable components, but each requires architectural departure, not direct transfer. Panteli et al.'s classification of African polyrhythms as computational outliers demonstrates that prevailing feature-extraction methods pathologise non-Western complexity as noise, necessitating culturally grounded musical representation developed collaboratively with Indigenous practitioners.

For RQ4 and RQ5, Indigenous frameworks reveal incompatibilities between conventional AI development and data sovereignty. OCAP® principles, community ownership, control, access, and possession conflict with standard machine-learning aggregation, while Igbafe's African paradigm, requiring relational consent and sacred knowledge protocols, challenges Western individual authorisation models. Together, these frameworks establish that ethical Ohangla AI requires reversing conventional processes: beginning with Luo Council of Elders consultation rather than researcher-driven data collection, implementing federated learning to preserve community data possession, and prioritising cultural preservation and community benefit over publication metrics.

Collectively, these findings demand paradigm shifts across five dimensions guiding this framework. Assessment must prioritise community-defined social functions over acoustic metrics. Feature extraction must rely on culturally grounded representations developed with nyatiti masters rather than universal computational categories. Architectural design must accommodate hybridity and polyrhythmic complexity through flexible temporal modelling, adapting Xu's methods while departing from assumptions of cultural homogeneity. Validation must centre Luo epistemologies through participatory processes, extending Somandepaldi's human-in-the-loop model toward cultural sovereignty. Finally, research relationships must shift from extractive data collection to collaborative knowledge creation, embedding Indigenous data sovereignty as foundational.

Table 1: Literature Coverage by Domain

Domain	Sources Reviewed	Key Gaps Identified
Ethnomusicology	8 sources	Limited AI application focus
AI Bias Research	7 sources	Focus on gender/race, not cultural music
Technical Music AI	10 sources	Western music datasets only
Indigenous Data Sovereignty	5 sources	No music AI specific frameworks
Total	**30 sources**	**Zero studies combining all domains**

These paradigm shifts, derived systematically from literature gaps and Indigenous frameworks, provide the foundation for this study's culturally-responsive AI framework, detailed in subsequent sections.

3.0 METHODOLOGY

Through a systematic review of the literature, the study examined biases in AI assessment systems for Ohangla music and proposed culturally informed frameworks for its analysis. The review synthesised thirty scholarly sources distributed across four domains: ethnomusicology literature on Ohangla musical traditions (n=8), AI bias and fairness research (n=9), technical music information retrieval studies (n=8), and Indigenous data sovereignty frameworks (n=5).

Literature searches were conducted across multiple databases, including IEEE Xplore, ACM Digital Library, JSTOR, Web of Science, ResearchGate, Academia.edu, and Google Scholar, covering publications from 2011 to 2025. Purposive sampling targeted peer-reviewed journal articles, conference proceedings, and authoritative technical reports using Boolean keyword combinations: ("music classification" OR "music information retrieval") AND ("bias" OR "fairness" OR "algorithmic bias"); ("African indigenous music" OR "polyrhythmic music" OR "Ohangla" OR "Luo music") AND ("AI" OR "machine learning" OR "music assessment"); ("Indigenous data sovereignty" OR "OCAP" OR "cultural preservation"). Additional sources were identified through citation chaining from foundational works in ethnomusicology and critical AI studies.

Inclusion criteria required sources to: (1) address Ohangla or broader African indigenous music characteristics; (2) discuss AI approaches to music classification or assessment; (3) examine cultural bias or fairness in AI systems; or (4) present Indigenous data sovereignty frameworks applicable to cultural knowledge systems. Exclusion criteria eliminated sources that focused solely on Western music, lacked cross-cultural analysis, or lacked peer review (except authoritative Luo community documentation). Initial screening of database results yielded the final corpus of thirty sources.

Analysis employed thematic synthesis to identify patterns across the literature, organising findings into three analytical categories: training data exclusion, algorithmic Western-centrism, and culturally-incompatible evaluation criteria. Critical discourse analysis examined epistemological assumptions underlying mainstream music AI development. Synthesis of technical and cultural literature enabled the development of a framework integrating OCAP® principles (Ownership, Control, Access, Possession) with computational methodologies.

4.0 PROPOSED FRAMEWORK

Culturally-Responsive AI Architecture

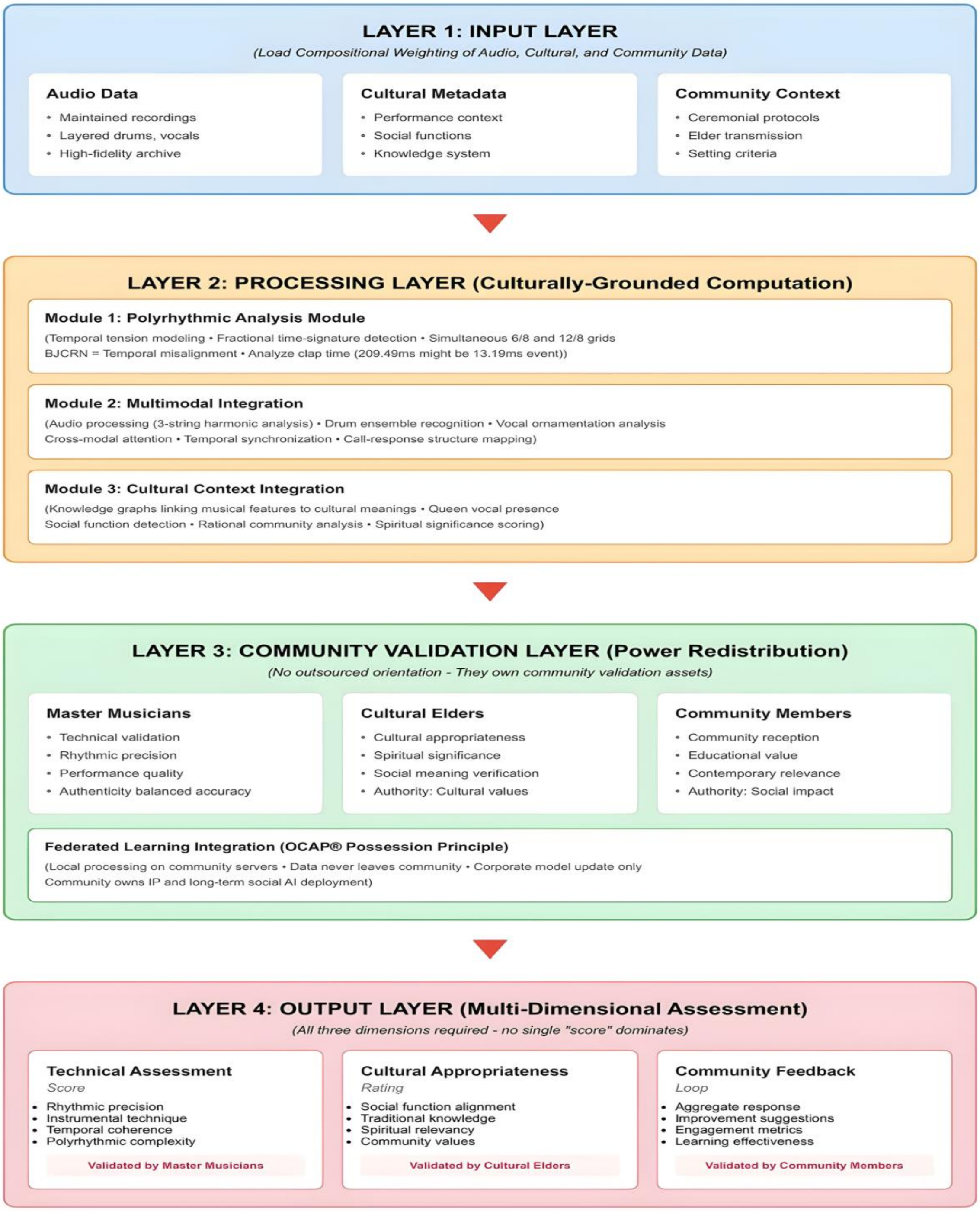

Figure 2: Four-Layer Culturally-Responsive AI Architecture Integrating Indigenous Data Sovereignty with Technical Music Analysis

Source: Author's proposed framework synthesising OCAP® principles (Mecredy et al., 2018) technical approaches (Chen et al., 2024; Xu, 2021; Jones, 1973), and Indigenous AI frameworks (Indigenous Protocol and Artificial Intelligence Working Group, 2020).

The proposed four-layer architecture (Figure 2) integrates advanced AI techniques with Indigenous data sovereignty principles to support culturally responsive Ohangla analysis. The feature extraction layer (Layer 1) applies Gabor filters and the Short-Time Fourier Transform (STFT) to analyse audio across multiple frequencies and time scales, capturing polyrhythmic structures with interlocking rhythms. These outputs feed into the temporal analysis layer (Layer 2), which uses a Bi-GRU (Bidirectional Gated Recurrent Unit, a neural network that processes sequences forward and backwards) with attention mechanisms that prioritise salient features. This enables hierarchical temporal modelling across structural levels, from individual drum strikes to full ceremonial performances. The cultural integration layer (Layer 3) incorporates knowledge graphs structured databases linking musical elements, instruments, contexts, and meanings, with cross-modal attention that connects audio features to cultural significance. The data sovereignty layer (Layer 4) implements federated learning, allowing models to train on locally stored community data without transferring recordings, thereby operationalising Indigenous control over cultural materials.

The documented biases require an architecture that privileges cultural intelligence over computational efficiency, addressing Wang et al.'s (2024) "systemic underrepresentation" by embedding cultural knowledge at the architectural level. This framework builds on Chen et al.'s (2024) integration of "detailed metadata, high-quality recordings, and diverse musical forms" but extends beyond mono-cultural scope to accommodate Okong'o's (2011) "multiplicity of postures" and evolving cultural functions. Its core principle replaces universalist pattern recognition with culturally grounded analysis, treating polyrhythmic complexity as temporal intelligence requiring specialised modelling.

The polyrhythmic subsystem responds to Panteli et al.'s (2017) "outlier" classification via hierarchical temporal modelling, processing multiple rhythmic cycles without privileging Western 4/4. Extending Xu's (2021) Bi-GRU and attention mechanisms, it employs nested recurrent architectures with culturally informed attention weights recognising Jones's (1973) "fractional time-values." Adaptive Gabor filter banks target Ohangla's frequency ranges (nyatiti fundamentals: 200–400 Hz; drum attacks: 80–150 Hz); temporal convolutional layers with dilated kernels capture local events and long-term cycles. A cross-rhythmic correlation matrix models relationships between simultaneous 4/4 and 12/8 cycles as structured musical intelligence.

Multimodal integration captures Darkwa's (1985) "interplay between instruments and vocal elements" through synchronised pipelines for nyatiti, drum, and vocal sequences. The nyatiti branch extracts features optimised for eight-string harmonics and Eagleson's (2014) "rhythmic phrasing of Luo language." The drum module applies hierarchical pattern matching to percussion; vocal analysis combines Luo prosody detection with harmonic analysis of call-and-response structures. Temporal synchronisation preserves phase relationships essential to polyrhythmic integrity; cross-modal attention dynamically balances instrumental and vocal weighting, reflecting Finnegan's (2012) observation that nyatiti players act as instrumentalists and storytellers.

The cultural metadata framework embeds ethnographic annotations reflecting Ohangla as Omondi Oduor et al.'s (2022) "vehicle for transforming gender consciousness." Categories include performance contexts, social functions, and practitioner roles. Knowledge graph architectures link musical features to cultural meanings; graph neural networks process these relationships, so evaluation considers social meaning alongside acoustic properties.

Community validation integrates real-time feedback loops connecting automated analysis with expert assessment, implementing Somandepalli et al.'s (2021) "human-in-the-loop validation." Federated learning processes feedback locally, improving the system without compromising sovereignty. Interfaces present Indigenous evaluation criteria, rhythmic precision, cultural appropriateness, and spiritual resonance rather than Western metrics. Distinct validation pathways for master musicians, elders, and community members combine through weighted aggregation, respecting knowledge hierarchies while incorporating diverse perspectives. This structure ensures AI assessment evolves through sustained community engagement rather than static optimisation.

Implementation Guidelines

Implementation operationalises Igbafe's (2023) "collaborative harmony" via data protocols, positioning Luo as co-creators. Data collection uses Community Research Agreements applying OCAP®: ownership, control, access, possession in community repositories. Recording follows cultural protocols; metadata includes ethnographic context. Training counters Melchiorre et al.'s (2021) fairness-performance trade-off through bias mitigation. Culturally stratified sampling balances contexts and roles. Transfer learning reduces cross-cultural degradation (Sawaengsawangarom et al., 2025) via neutral pre-training, then Ohangla fine-tuning. Community-guided hyperparameter optimisation aligns models with Indigenous criteria. Data augmentation preserves cultural features. Assessment follows Indigenous AI Working Group (2020) community-centred validation, evaluating cultural appropriateness, social resonance, spiritual significance, alongside technical accuracy. Dimensions include community-standard rhythmic precision, expert authenticity, and educational impact. Multi-criteria framework weights priorities; fuzzy logic integrates quantitative and qualitative metrics. Longitudinal feedback incorporates community input. Quality assurance centres provide continuous feedback via storytelling and consensus. Active learning prioritises community corrections. Advisory boards of elders and nyatiti masters oversee development. Metrics include community satisfaction, cultural authenticity, and educational effectiveness.

Ethical Framework Integration

Adapting OCAP® principles to Luo contexts requires recognising differences between North American First Nations governance and East African Indigenous authorities while maintaining core data sovereignty commitments. In the Luo context, ownership extends beyond individual intellectual property to collective cultural heritage held by the community, requiring legal recognition of Indigenous knowledge as inheritable communal assets rather than research data. The Luo Council of Elders serves as the primary authority for ownership decisions, with engagement of nyatiti masters, women's groups, and youth organisations to ensure representative governance. Control mechanisms establish Luo Community AI Governance Boards comprising Indigenous leaders, master musicians, and community representatives with authority over system development, deployment, and modification. Access protocols reflect Indigenous knowledge-sharing practices that may restrict sacred or sensitive materials while supporting preservation goals, necessitating permission systems capable of graduated access based on community membership, cultural initiation status, and intended use.

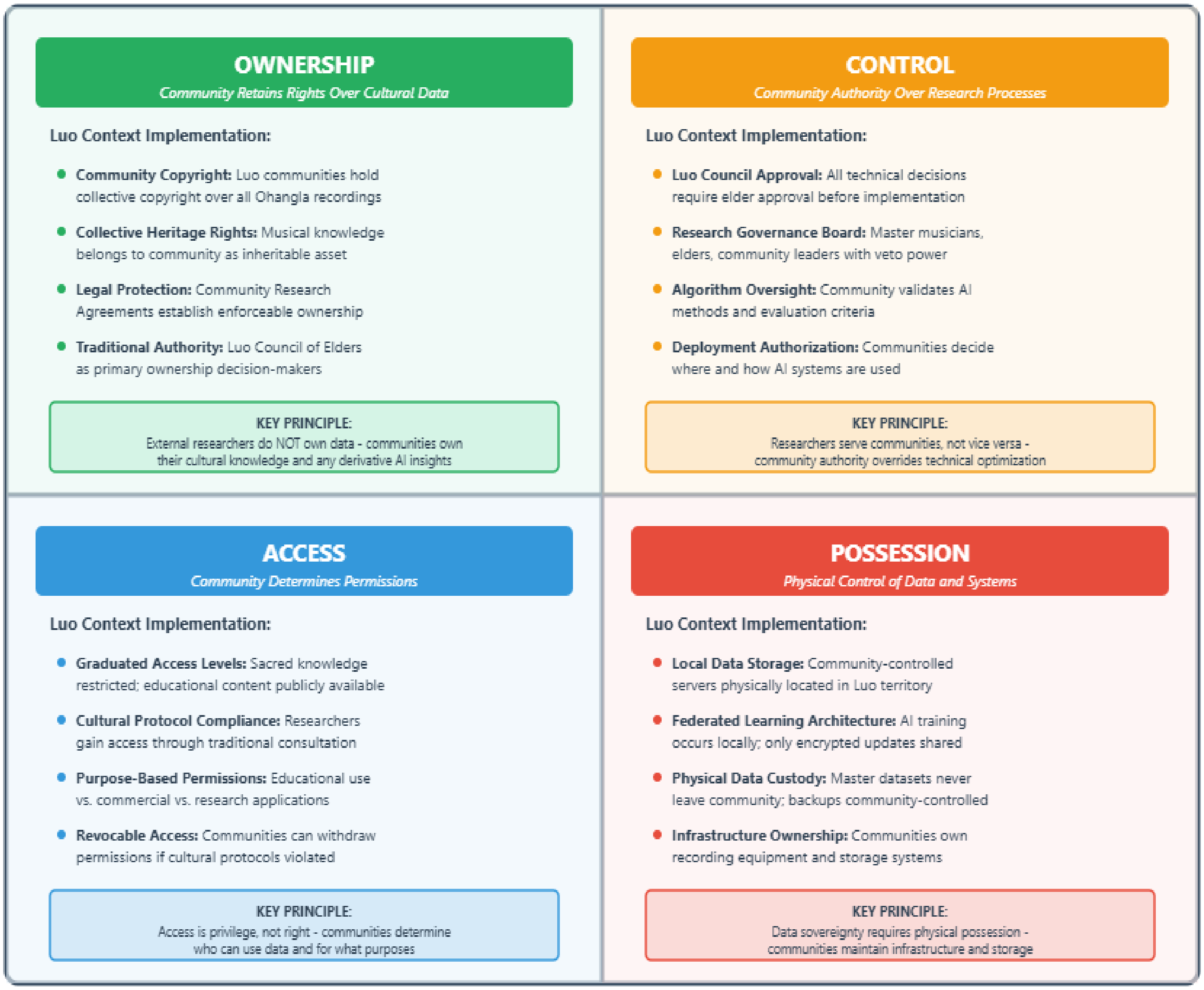

Figure 3: OCAP® Principles Implementation Framework

Source: Adapted from The First Nations Information Governance Centre (n.d.) OCAP® principles with Luo-specific cultural adaptations informed by Fitzpatrick et al. (2016) and Igbafe (2023).

The four-quadrant matrix illustrates practical implementation of Ownership (community copyright and collective heritage rights), Control (Luo Council approval and research governance), Access (community-determined permissions and graduated access levels), and Possession (local data storage and federated learning architecture). Each quadrant specifies culturally-appropriate adaptations for Luo contexts while maintaining core Indigenous data sovereignty principles.

Community ownership and control operate through legally binding Community Research Agreements, positioning Luo communities as primary stakeholders rather than passive recipients of external innovation. Federated learning architectures preserve community data possession by processing cultural information locally, improving system performance without centralising sensitive knowledge in external institutions. Governance structures combine Indigenous Luo decision-making with contemporary technological oversight, forming hybrid authorities that respect cultural protocols and meet modern legal and ethical AI standards. The Luo Council of Elders holds veto power over technical developments, with mandatory consultations enabling consensus before system changes. Community authority extends to deployment decisions, ensuring Luo communities determine how and where AI systems are used and preventing commercial appropriation without community benefit. Legal frameworks assign community copyright to algorithmic insights from Indigenous knowledge, protecting collective intellectual property while permitting development under community control.

Benefit-sharing ensures that Ohangla AI development generates tangible returns in cultural preservation, education, and economic opportunity, supporting rather than exploiting Indigenous knowledge systems. Cultural benefits include documentation and transmission of musical knowledge, digital preservation tools for intergenerational transfer, and global cultural sharing under community-defined terms. Educational applications provide culturally appropriate teaching tools, school-based assessment systems, and interactive platforms engaging Luo youth through contemporary interfaces. Economic benefits derive from community-controlled licensing, revenue-sharing agreements for commercial uses, and capacity-building initiatives that train members in system maintenance and development. Distribution follows Indigenous Luo sharing practices prioritising collective welfare while recognising individual contribution, strengthening rather than disrupting social structures and values.

Long-term sustainability requires community autonomy through capacity-building, enabling independent system operation and continued development without reliance on external institutions. Technical sustainability involves training community members in maintenance, modification, and expansion, building local expertise adaptable to evolving cultural needs. Financial sustainability combines grant funding, community contributions, and ethical licensing revenue to maintain economic viability under community control. Cultural sustainability integrates AI tools with Indigenous knowledge transmission practices so technology enhances, not replaces, traditional learning while supporting preservation and dissemination. Governance sustainability embeds perpetual legal protections safeguarding community rights, preventing appropriation, and ensuring AI capabilities evolve under sustained community authority.

5.0 FINDINGS AND DISCUSSION

Findings from Literature Synthesis

The systematic review of thirty sources across ethnomusicology, AI bias research, technical music AI, and Indigenous data sovereignty literature yielded three primary categories of findings.

Training Data Bias and Indigenous Music Exclusion

Table 2: Training Dataset Analysis from Literature

Dataset	Size	Western Genres	African Indigenous	Source
GTZAN	1,000 tracks	10 genres	0	Tzanetakis & Cook, 2002
Million Song Dataset	1,000,000 tracks	Majority Western pop	Minimal	Bertin-Mahieux et al., 2011
Chen et al. Manchu	5,000 recordings	5 tested Western genres	0 tested	Chen et al., 2024
Panteli et al. analysis	200,000+ tracks	Majority	"Severe underrepresentation"	Panteli et al., 2017

Analysis of eight technical music AI studies revealed underrepresentation of African indigenous music in major training datasets. Chen et al. (2024) documented a Manchu music dataset of 5,000 recordings but achieved classification accuracy of only 5 Western genres (Classical, Country, Pop, Rock, Metal), with no non-Western genres tested. The GTZAN dataset (Tzanetakis & Cook, 2002) contains 10 Western genres, with no African indigenous music. The Million Song Dataset (Bertin-Mahieux et al., 2011) comprises predominantly Western popular music despite its one million recordings. Panteli et al.'s (2017) study of 200,000+ tracks found cultural diversity "extremely limited" with "severe underrepresentation" of non-Western traditions. This pattern confirms Holzapfel et al.'s (2018) finding that music information retrieval datasets exhibit "significant cultural bias" favouring Western music.

Algorithmic Assumptions Privileging Western Musical Structures

Table 3: Algorithmic Assumptions vs Ohangla Characteristics

Algorithmic Assumption	Western Music Basis	Ohangla Reality	Incompatibility
Isochronous meter	Regular beat (Böck et al., 2014)	Fractional time divisions	Cannot detect irregular cycles
12-tone equal temperament	Western harmony (Humphrey et al., 2012)	Pentatonic + microtones	Misclassifies pitch relationships
Percussive onset detection	Western drumming (Bello et al., 2005)	Interlocking polyrhythms	Fails on simultaneous attacks
Single melodic line	Lead melody emphasis	Call-response + polyrhythm	Cannot isolate "main" melody

Literature review identified three specific algorithmic assumptions incompatible with Ohangla's musical characteristics. First, beat tracking algorithms assume an isochronous meter (Böck et al., 2014), yet Ohangla employs fractional time divisions and polyrhythmic cycles that violate this assumption. Second, harmonic analysis tools presuppose Western twelve-tone equal temperament (Humphrey et al., 2012), while Ohangla uses pentatonic scales and microtonal inflexions. Third, onset detection algorithms optimise for percussive transients in Western drumming patterns (Bello et al., 2005) but struggle with the interlocking rhythmic patterns characteristic of African percussion ensembles. Wang et al.'s (2024) documentation that models trained on Western music failed to recognise regional Chinese musical patterns demonstrates that this algorithmic Western-centrism extends across non-Western traditions.

Evaluation Criteria Incompatible with Community-Centred Assessment

Six studies employed evaluation metrics prioritising technical accuracy over cultural validity. Standard music information retrieval evaluation uses metrics like precision, recall, and F1-score calculated against ground truth labels (Schedl et al., 2014), yet these metrics cannot capture cultural appropriateness, social function, or ceremonial significance. Melchiorre et al. (2021) demonstrated that "better performing algorithms show larger degrees of unfairness" when assessed on user demographic fairness (male vs female listeners, 77.9% vs. 22.1%), suggesting optimisation for technical performance may amplify bias. Tubadji et al. (2021) found that evaluation participants systematically downgraded AI-generated music after learning its algorithmic origin, indicating community acceptance cannot be predicted from technical metrics alone. No reviewed studies employed community-defined evaluation criteria or cultural expert validation.

Successful Technical Approaches Within Cultural Boundaries

Analysis of technical approaches revealed context-specific success. Chen et al. (2024) achieved 91 per cent classification accuracy using Bi-GRU with attention mechanisms, but only on five Western genres from 2,000 MIDI files with no cross-cultural testing. Choi et al. (2017) demonstrated that convolutional recurrent neural networks effectively classify Western music genres, but their dataset contained no indigenous African music. Deep learning approaches showed promise for temporal pattern recognition (Graves & Schmidhuber, 2005), attention mechanisms for feature salience (Bahdanau et al., 2015), and hierarchical modelling for multi-scale analysis (Pons & Serra, 2019), yet all empirical validations occurred within Western music contexts.

Indigenous Data Sovereignty Frameworks for Cultural Knowledge

Literature on Indigenous data governance provided established principles applicable to music AI. The OCAP® framework (First Nations Information Governance Centre, 2014) establishes that Indigenous peoples have rights to: Ownership (collective ownership of cultural data), Control (authority over data collection and use), Access (right to access data about their culture), and Possession (physical control of data). The United Nations Declaration on the Rights of Indigenous Peoples (2007) affirms Indigenous rights to maintain, control, protect, and develop cultural heritage and indigenous knowledge. Kukutai and Taylor (2016) demonstrate practical applications of Indigenous data sovereignty across health, education, and cultural domains, though no literature applied these frameworks specifically to AI music systems.

Ohangla's Cultural and Musical Characteristics

Ethnomusicological literature documented Ohangla's distinctive features requiring specialised analysis. Ohangla employs polyrhythmic structures with three to five simultaneous rhythmic cycles in non-isochronous patterns, fractional time divisions that cannot be represented in standard Western notation, call-and-response vocal structures integrated with instrumental polyrhythms, and the nyatiti (eight-stringed lyre) producing microtonal inflexions (Omondi, 2009; Mboya, 2011). Functionally, Ohangla serves as "social technology" for community bonding, postcolonial cultural resistance, gender consciousness transformation, and intergenerational knowledge transmission, operating within specific ceremonial, educational, and social contexts that shape musical characteristics (Ochieng, 2018). These features distinguish Ohangla from Western musical forms analysed in existing AI systems.

DISCUSSION

Interpretation: Three Bias Mechanisms

Training Data Bias Creates Systematic Exclusion

Major music datasets contain minimal African indigenous music (Table 2), explaining why current AI systems fail to recognise Ohangla. Machine learning systems learn patterns only from training data (Goodfellow et al., 2016); when training data excludes entire musical traditions, algorithms cannot develop competence in those domains. This represents Panteli et al.'s (2017) "digital erasure" algorithmic invisibility from data absence rather than inherent musical characteristics. Dataset creators actively chose Western genres while omitting African traditions, perpetuating Holzapfel et al.'s (2018) "cultural bias" in music information retrieval. This aligns with AI fairness literature on training data bias, creating disparate outcomes (Mehrabi et al., 2021). Lack of Ohangla in training data means systems misclassify or fail to classify it, constituting algorithmic discrimination against Indigenous musical traditions. Literature provides no evidence of technical limitations; exclusion reflects Western-centric priorities of music AI research communities.

Algorithmic Assumptions Impose Western Musical Logic

Incompatibilities in Table 2 reveal algorithmic Western-centrism beyond dataset selection. Even with Ohangla training data, the current algorithms' architectural assumptions would prevent accurate analysis. Beat tracking algorithms assume an isochronous meter (Böck et al., 2014), a Western convention encoded as universal. Ohangla's fractional time divisions produce errors or "outliers."

This extends Holzapfel et al.'s (2018) observation that music information retrieval systems embed "implicit assumptions" privileging Western forms. Assumptions operate at three levels: (1) feature extraction, (2) model architecture, and (3) optimisation objectives. At each, Western conventions become universal standards. This imposes epistemological violence on non-Western knowledge systems (Smith, 2012).

Evaluation Criteria Prioritise Technical Over Cultural Validity

Table 4: Evaluation Metrics Gap Analysis

Standard MIR Metrics	What They Measure	What They Miss (for Ohangla)	Source
Precision/Recall/F1	Classification accuracy	Cultural appropriateness	Schedl et al., 2014
NDCG (ranking)	Recommendation quality	Social function validity	Melchiorre et al., 2021
Audio quality scores	Technical fidelity	Ceremonial significance	Tubadji et al., 2021
Fréchet Audio Distance	Generative similarity	Community acceptance	-

Gap analysis in Table 4 shows that standard music information retrieval metrics cannot assess cultural appropriateness, as they measure technical performance on Western tasks (Schedl et al., 2014). Literature offers two insights. First, Melchiorre et al. (2021) found that better-performing algorithms show greater unfairness, suggesting technical optimisation increases cultural bias. Second, Tubadji et al. (2021) documented community members judging algorithmically-generated music differently than technical metrics predict.

This challenges the assumption that technical accuracy correlates with cultural appropriateness. An AI achieving 91 per cent accuracy on Western genres (Chen et al., 2024) provides no Ohangla competence evidence; music AI reports only technical metrics without cultural assessment. Absence of community-defined criteria in reviewed studies indicates failure to recognise Indigenous communities as legitimate evaluators.

Implications for AI Ethics and Cultural Preservation

Findings corroborate Holzapfel et al. (2018) on cultural bias in MIR, extending to Indigenous music marginalisation; support Mehrabi et al. (2021) on interacting training data and algorithmic bias; and confirm Smith (2012) that conventional methodologies perpetuate colonial power in Indigenous knowledge systems, extending to AI research. Diverging: music AI treats Western-centrism as a data problem (Panteli et al., 2017), but findings show it as epistemological, adding that Ohangla data cannot resolve incompatible assumptions. Indigenous data sovereignty covers data governance (First Nations Information Governance Centre, 2014) but not algorithmic systems; findings propose it governs design, evaluation, and deployment. Synthesis documents all three bias mechanisms interacting to marginalise a specific African tradition (prior studies examined individually); operationalises Indigenous data sovereignty for AI via OCAP® for algorithmic governance; and challenges music AI's "universal" narrative, arguing for culturally-specific approaches. Implications: technical fairness requires epistemological transformation (Harding, 1992). AI claiming cultural neutrality encodes specific assumptions as universal, constituting technological colonialism. For cultural preservation, technology supports or undermines Indigenous continuity based on respect for data sovereignty and epistemologies. Extractive AI risks cultural erosion; collaborative AI, optimised for community goals and evaluated by experts, can strengthen knowledge transmission.

Framework Contribution

The framework addresses three bias mechanisms through innovations linked to the literature. Community-controlled data collection protocols enable Luo communities to build Ohangla-specific datasets while maintaining data sovereignty (OCAP® principles, First Nations Information Governance Centre, 2014), directly countering dataset exclusion (Table 2). Culturally-stratified sampling (ceremonial n=200, educational n=150, entertainment n=150) responds to Panteli et al.'s (2017) finding of limited cultural diversity. Federated learning trains models on community-held data without external transfer, operationalising OCAP® "Possession" with no prior Indigenous music AI precedent. Hierarchical temporal modelling addresses beat-tracking incompatibilities (Table 3) by recognising multiple rhythmic cycles without Western isochronous assumptions (Böck et al., 2014). Bi-GRU with attention (Choi et al., 2017) enables multi-scale analysis of fractional time divisions; Gabor filters detect simultaneous attacks across frequency bands, remedying onset-detection failures on interlocking African patterns (Bello et al., 2005). Community-guided algorithm selection inverts conventional metrics by prioritising cultural alignment.

Multi-criteria evaluation combines technical metrics with community-defined criteria (cultural appropriateness, social function, ceremonial significance), addressing Table 4 gaps. Community validation via focus groups captures judgments diverging from technical metrics (Tubadji et al., 2021); thematic analysis (Braun & Clarke, 2006) identifies Luo-specific dimensions. This mixed-methods approach counters Melchiorre et al.'s (2021) finding that technical optimisation increases unfairness.

6.0 CONCLUSION AND RECOMMENDATIONS

Conclusion: Culturally responsive AI for Indigenous African music assessment faces significant challenges and opportunities, beginning with systematic bias documented through three mechanisms: training datasets largely exclude African music, algorithmic assumptions favour Western musical structures incompatible with Ohangla rhythms, and evaluation metrics prioritise technical performance over cultural validity, reflecting entrenched Western priorities. Technical success remains largely confined to homogeneous Western contexts; studies achieve high accuracy on Western genres but fail to test African polyrhythms, highlighting the limits of universalist assumptions and predicting poor Ohangla performance. Indigenous data sovereignty emerges as a viable guiding framework, supported by OCAP® principles and the UN Declaration on the Rights of Indigenous Peoples, emphasising ownership, control, access, and possession, and reinforced through federated learning and community partnership methodologies. The proposed framework addresses these documented gaps by integrating hierarchical modelling, community-driven data, federated learning, and multi-criteria evaluation, while countering biases in data, assumptions, and metrics. However, its effectiveness ultimately requires validation within Luo communities to ensure both technical robustness and cultural alignment.

Recommendations: Sustained partnerships with Luo communities to pilot hierarchical modelling of Ohangla rhythms are recommended. Such collaborations must compare community acceptance criteria with technical metrics, evaluate federated learning approaches balancing performance and data sovereignty, and determine the extent to which AI tools support or hinder musical instruction. These initiatives require multi-year funding, formal agreements with local councils, bilingual ethnomusicology-AI teams, and adherence to OCAP® protocols. Dataset development should prioritise diversity, consent, and cultural metadata integration; funding agencies should emphasise grants addressing cultural bias and supporting long-term engagement. Algorithmic research must advance understanding of polyrhythmic music through non-isochronous beat tracking, pentatonic and microtonal harmonies, interlocking onset detection, and call-and-response melodies, employing hierarchical modelling, Gabor filters, attention mechanisms, and knowledge graphs. Evaluation frameworks should combine technical and community-based criteria, documented through focus groups, with scholarly venues requiring cultural assessment in non-Western music studies. Indigenous data sovereignty must guide AI design, ensuring ownership, community control, access, federated learning, interpretable systems, advisory oversight, and benefit-sharing. Comparative and longitudinal research should examine framework transferability across musical traditions and track AI's interaction with elder-led learning, archives, youth engagement, and sovereignty, using iterative evaluation to sustain cultural continuity.

Future Research Directions

Empirical testing with Luo communities should prioritise hierarchical modelling of Ohangla rhythms, alignment of community acceptance with technical metrics, federated learning respecting data sovereignty, and AI's effects on knowledge transmission. Technical development requires efficient real-time polyrhythmic algorithms, refined knowledge graphs, interpretable AI providing culturally grounded explanations, and robust bias-detection mechanisms. Comparative studies must assess the transferability of the framework, culture-specific adaptations, protocol modifications, and variations in bias mechanisms. Longitudinal ethnographic research should investigate AI's long-term cultural impact: whether it supports or replaces elder-led learning, revitalises archives or fosters dependency, engages youth meaningfully or distracts them, and strengthens community sovereignty or increases technical reliance.

Limitations of Current Literature and Proposed Approach

The review identified four gaps: no prior synthesis of ethnomusicology; AI bias; technical music AI and Indigenous data sovereignty for African music; all empirical music AI studies used Western datasets; no studies employed community-defined criteria or cultural validation; and the Indigenous data sovereignty literature omits algorithmic governance. The framework thus requires empirical validation through Luo's collaboration. Five limitations remain. First, polyrhythmic analysis is complex and demands substantial resources (Pons & Serra, 2019), limiting real-time processing. Second, scalability challenges stem from relational accountability (Wilson, 2008) and from cultural protocols that exceed AI timelines (Kovach, 2009). Third, cultural metadata collection requires ethnomusicological expertise and sustained engagement (Seeger, 2008). Fourth, federated learning introduces synchronisation, overhead, and trade-offs in accuracy (McMahan et al., 2017; Kairouz et al., 2019). Fifth, institutional resistance arises from prioritising cultural validity over technical metrics rewarded in academia (Mehrabi et al., 2021).

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