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ARTICLE

DATA-DRIVEN EDUCATIONAL INTELLIGENCE FOR CULTURAL HERITAGE TRAINING: A BLENDED LEARNING FRAMEWORK FOR MINORITY DANCE EDUCATION

INTELIGÊNCIA EDUCACIONAL BASEADA EM DADOS PARA A FORMAÇÃO EM PATRIMÓNIO CULTURAL:UM MODELO DE APRENDIZAGEM HÍBRIDA PARA A EDUCAÇÃO DA DANÇA DE MINORIAS

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ABSTRACT

Purpose: Minority dance traditions represent significant forms of cultural heritage that are preserved through educational transmission. However, their sustainability is increasingly challenged by limited expert instructors, geographic barriers, and evolving learner preferences in digital learning environments. In response to these challenges, this study proposes a data-driven blended learning framework for minority dance education that integrates traditional instruction with digital platforms while generating analytical insights to support educational intelligence and institutional decision-making.

Methodology/approach: The framework incorporates motion capture technology with an Artificial Gorilla Troop Optimized Conditional Variational Autoencoder (AGTO-CVAE) to enable accurate analysis and recognition of students' dance movements. Data were collected from students enrolled in minority dance programs through structured questionnaires, performance evaluations, and online engagement metrics. Motion capture sequences were normalized prior to analysis. Exploratory Factor Analysis (EFA) was applied to identify latent dimensions of the blended learning environment, and K-means clustering was used to group learners according to technological adaptability, engagement, and cultural orientation.

Originality/Relevance: The framework integrates traditional instruction with digital platforms while generating analytical insights to support educational intelligence and institutional decision-making in minority dance education.

Key findings: Experimental results show that the proposed AGTO-CVAE model achieves superior performance, with precision of 0.9875, recall of 0.9845, and an F1-score of 0.9859, while reducing computational complexity.

Theoretical/methodological contributions: The findings demonstrate that data-driven blended learning environments can function as educational intelligence systems, supporting improved instructional design, learner engagement, and sustainable cultural heritage education.

Keywords: Digital Blended Learning. Cultural Education Intelligence. Minority Dance Education. Exploratory Factor Analysis. Cluster Analysis. Educational Data Analytics.

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RESUMO

Objetivo: As tradições de dança de minorias representam formas significativas de patrimônio cultural que são preservadas por meio da transmissão educacional. No entanto, sua sustentabilidade é cada vez mais desafiada pela escassez de instrutores especializados, barreiras geográficas e mudanças nas preferências dos aprendizes em ambientes digitais de aprendizagem. Em resposta a esses desafios, este estudo propõe um framework de aprendizagem híbrida orientado por dados para a educação em dança de minorias, integrando o ensino tradicional com plataformas digitais e gerando insights analíticos para apoiar a inteligência educacional e a tomada de decisão institucional.

Metodologia/Abordagem: O framework incorpora tecnologia de captura de movimento com um Autoencoder Variacional Condicional otimizado por Artificial Gorilla Troop (AGTO-CVAE) para permitir a análise e reconhecimento precisos dos movimentos de dança dos estudantes. Os dados foram coletados de alunos matriculados em programas de dança de minorias por meio de questionários estruturados, avaliações de desempenho e métricas de engajamento online. As sequências de captura de movimento foram normalizadas antes da análise. A Análise Fatorial Exploratória (AFE) foi aplicada para identificar dimensões latentes do ambiente de aprendizagem híbrida, e o algoritmo K-means foi utilizado para agrupar os aprendizes conforme adaptabilidade tecnológica, engajamento e orientação cultural.

Originalidade/Relevância: O framework integra o ensino tradicional com plataformas digitais, ao mesmo tempo em que gera insights analíticos para apoiar a inteligência educacional e a tomada de decisão institucional no contexto da educação em dança de minorias.

Principais Resultados: Os resultados experimentais demonstram que o modelo AGTO-CVAE proposto apresenta desempenho superior, com precisão de 0,9875, recall de 0,9845 e F1-score de 0,9859, além de reduzir a complexidade computacional.

Contribuições Teóricas/Metodológicas: Os achados indicam que ambientes de aprendizagem híbrida orientados por dados podem funcionar como sistemas de inteligência educacional, promovendo melhorias no design instrucional, no engajamento dos estudantes e na sustentabilidade da educação do patrimônio cultural.

Palavras-chave: Aprendizagem Híbrida Digital. Inteligência Educacional Cultural. Educação em Dança de Minorias. Análise Fatorial Exploratória. Análise de Cluster. Análise de Dados Educacionais.

1 INTRODUCTION

Minority dance represents a significant form of cultural heritage that embodies the historical traditions, belief systems, and social identity of communities through rhythm, movement, and symbolic expression developed across generations (Kavecsánszki, 2023). These dance traditions function as living cultural narratives that preserve social values and ancestral knowledge, allowing performers to become carriers of cultural identity that extend beyond aesthetic performance to deeper cultural meaning (Wang, 2024). The patterns of movement, costumes, music, and spatial formations in minority dances communicate cultural stories that strengthen a shared sense of belonging and collective heritage among practitioners and audiences (Mabingo et al., 2024). Through embodied learning experiences, minority dance education promotes deeper cultural understanding by linking physical practice with emotional sensitivity, cultural awareness, and the transmission of traditional knowledge (Shi, 2022).

As an evolving art form, minority dance contributes to cultural continuity while adapting to changing social and educational contexts (Peng, 2022). Education plays a critical role in this process by providing structured environments through which learners acquire knowledge, skills, and cultural values while supporting cognitive development and personal growth (Crum, 2024). Contemporary learning processes emphasize interaction, reflection, and experiential engagement, enabling learners to construct knowledge actively rather than passively receiving information (Hung, 2023). In the context of cultural education, effective learning involves not only technical skill acquisition but also interpretation, appreciation, and emotional engagement with cultural practices (Lei, 2024). Consequently, modern educational frameworks increasingly adopt learner-centered approaches that encourage autonomy, motivation, and sustained engagement through flexible and inclusive learning environments (Ding, 2024). These approaches support deeper understanding, long-term knowledge retention, and meaningful connections between learning experiences and cultural identity formation (Coudenys et al., 2024).

Recent technological advancements have introduced digital tools and intelligent systems into dance education. For example, automated dance style identification using short video clips has been explored through fine-grained classification techniques, channel attention mechanisms, and autoencoder-based models (Guo et al., 2025). These approaches demonstrate promising accuracy in movement recognition but remain highly dependent on video quality and provide limited capability for comprehensive performance evaluation. Similarly, studies on blended learning environments highlight the importance of interpersonal interaction and collaborative participation in online learning communities (Hod & Dvir, 2022). Although such approaches enhance learner engagement, they often face contextual limitations and difficulties in scaling across larger or less interactive digital learning environments.

Despite these developments, existing approaches in minority dance education face several limitations. Many systems rely heavily on video-based analysis, lack integrated automated evaluation mechanisms, and encounter challenges related to scalability and adaptability in diverse learning contexts. Furthermore, current models rarely utilize educational data systematically to support instructional improvement or strategic decision-making in cultural education systems.

To address these limitations, this study proposes a data-driven blended learning model for minority dance education that integrates traditional face-to-face instruction with digital learning technologies. The proposed framework incorporates motion capture technology and an Artificial Gorilla Troop Optimized Conditional Variational Autoencoder (AGTO-CVAE) to enable precise recognition and analysis of students' dance movements. By combining intelligent motion analysis with learning analytics, the framework supports personalized learning experiences while generating performance data that can inform instructional design and educational management. Ultimately, the model aims to enhance cultural knowledge transmission, learner engagement, and skill development while supporting sustainable minority dance education in digital learning environments. Figure 1 illustrates the integration of traditional instruction and digital learning components within the proposed minority dance education framework.

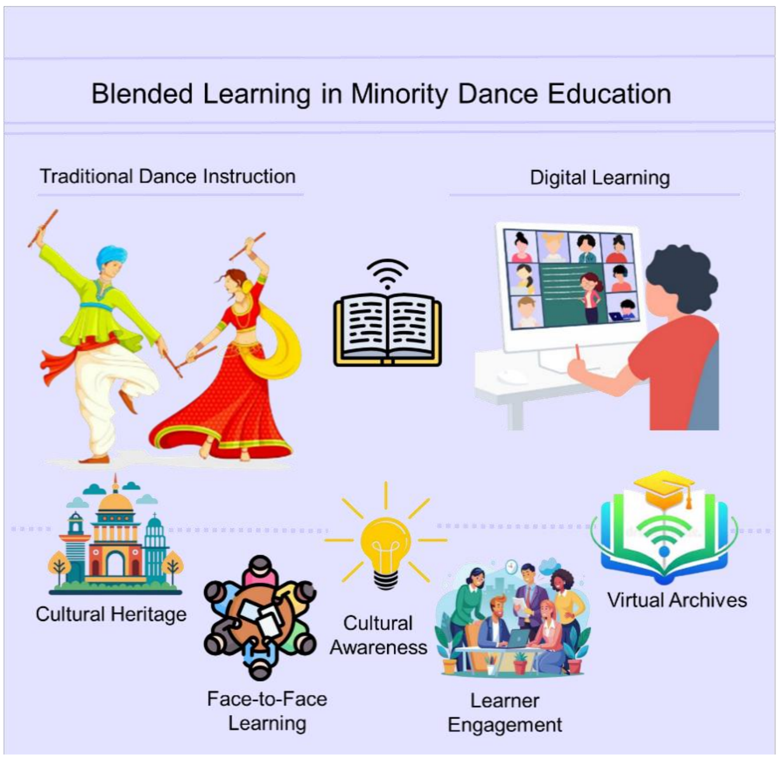

Figure 1: Conceptual overview of blended learning framework for minority dance education

1.1 Key contributions

This study makes several important contributions to the advancement of minority dance education through the integration of digital technologies and data-driven learning analytics.

The study integrates the Artificial Gorilla Troop Optimized Conditional Variational Autoencoder (AGTO-CVAE) with Exploratory Factor Analysis (EFA) and K-means clustering, enabling precise movement recognition, performance assessment, and identification of key learning dimensions within blended learning environments.

Preprocessing involved Z-score normalization to standardize motion capture sequences and survey responses, ensuring a uniform representation across features for accurate analysis.

The AGTO-CVAE method employeding for movement analysis alongside Exploratory Factor Analysis (EFA) and K-means clustering, enables precise performance assessment and identification of key learning dimensions.

The results demonstrated improvements in technical proficiency, cultural awareness, learner engagement, and accessibility, validating the effectiveness of the blended learning approach in preserving minority dance traditions.

2 RELATED WORKS

This section reviews previous studies related to blended learning, cultural dance education, and intelligent movement analysis systems. The review summarizes key findings from prior research, identifies methodological approaches used in the literature, and highlights existing limitations that motivate the development of the proposed framework.

Guang and Xueliang (2025) investigated the influence of blended learning approaches on higher-level folk dance education using an experimental design. Their findings indicate that immersive and interactive learning environments significantly improve educational effectiveness and learner engagement. However, the study is limited by its context-specific implementation and the absence of long-term longitudinal evaluation.

Catalano and Morales (2022) examined Arts and Community-Based (ACB) approaches in intercultural teacher education programs involving immigrant and diverse student populations. Through thematic analysis of reflections from 61 participants, the study found that ACB experiences promote empathy, shared understanding, and critical awareness among learners. These experiences enable students to challenge social inequalities and support inclusive educational practices.

Qian and Saearani (2025) explored the integration of cultural values within traditional Chinese dance education through curriculum and policy analysis. Their findings reveal that cultural dimensions are often underemphasized due to the prioritization of technical and performance-oriented training. The study also highlights challenges such as resistance to pedagogical innovation, while suggesting that interdisciplinary and digital learning approaches may enhance cultural awareness and support cultural heritage preservation.

Ju (2025) proposed a deep learning approach for dance pose estimation using Fusion-based Global Dance Pose Patterns. This method improves classification accuracy, precision, and generalization in dance movement recognition. Experimental results demonstrate strong real-time performance across multiple dance applications. Nevertheless, the effectiveness of the model is limited by dataset diversity and variability in real-world dance styles.

Zheng et al. (2024) developed a teacher training framework based on the principles of dance education and embodied learning. Using critical discourse analysis of national policy documents and international research, the study demonstrates how movement-based pedagogy can support cognitive, social-emotional, and cultural learning. The framework contributes to the development of culturally responsive educators with improved pedagogical preparedness and international applicability.

Zhang and Wang (2024) proposed a technology-enabled dance teaching evaluation system that integrates facial emotion recognition and motion-based movement analysis within blended learning environments. The results indicate improved assessment accuracy and more effective instructional feedback. However, the approach requires sophisticated sensing technologies and may face challenges in scalability across diverse learning contexts.

Zhen and Keun (2025) investigated the use of smart movement recognition technologies for teaching ethnic dance forms. Their approach utilizes a 3D-ResNet architecture to classify multi-ethnic dance movements. The findings demonstrate high recognition accuracy and adaptability across different dance styles. However, the model relies heavily on curated datasets and encounters difficulties in real-time implementation within varied instructional environments.

Overall, existing studies highlight the growing integration of digital technologies and artificial intelligence in dance education. However, many current approaches remain limited by dataset constraints, technological dependencies, and insufficient integration of cultural learning objectives within intelligent educational systems. These limitations indicate the need for more comprehensive frameworks that combine cultural education, intelligent movement analysis, and data-driven learning environments to support effective minority dance education.

2.1 Research gap

The literature focuses on immersive technologies, community-based pedagogies, cultural policy insights, pose -estimation methods, andor teacher training models singly. Such investigations do not have not developed an education model thatwhich connects cultural transmission and personalized learning in the context of minority dance education. In addition, low flexibility between learner profiles and athe lack of correspondence between cultural meaning and learning formations are still apparent. These gaps highlight the need for a more integrated approach that combines cultural education, intelligent movement analysis, and adaptive learning strategies. To address these limitations, the present study proposes a data-driven blended learning model that integrates traditional cultural instruction with intelligent movement analysis. The proposed framework incorporates the Artificial Gorilla Troop Optimized Conditional Variational Autoencoder (AGTO-CVAE) to support precise movement representation while combining learner-centered analytics to enhance instructional adaptability. By linking cultural learning objectives with intelligent data analysis, the proposed model aims to support cultural continuity, learner engagement, and personalized instruction in minority dance education.

3 METHOD

The objective of this study is to enhance minority dance education by promoting cultural transmission, improving learner engagement, and strengthening technical skill development through a data-driven blended learning approach. The proposed methodology integrates traditional face-to-face instruction with digital learning technologies to create a flexible and interactive educational environment that supports both cultural understanding and skill acquisition.

The blended learning model combines classroom-based dance instruction with online learning resources, including digital video demonstrations, virtual cultural materials, and interactive learning platforms. This integration allows learners to access instructional content beyond physical classroom settings while maintaining the cultural authenticity and embodied learning experience that are essential to minority dance education.

To support accurate movement analysis and performance evaluation, the framework incorporates motion capture technology combined with an Artificial Gorilla Troop Optimized Conditional Variational Autoencoder (AGTO-CVAE). This model enables precise representation and recognition of dance movements, allowing the system to analyze learner performance and generate analytical feedback that supports both teaching and learning processes. Figure 2 depicts the AGTO-CVAE-–based blended learning architecture that integratesing motion capture, digital resources, and performance analytics for minority dance training.

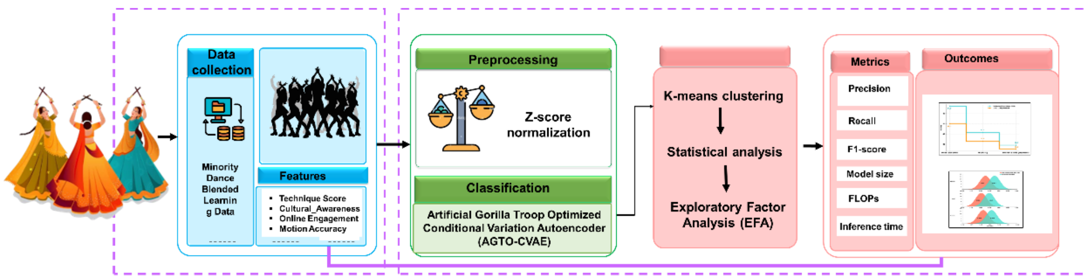

Figure 2: Integrated AGTO-CVAE blended learning framework for minority dance analytics.

3.1 Data collection

The Minority Dance Blended Learning Data wereis collected from an open source Kaggle. This dataset contains 19,385 learner records and, supports blended learning research in minority dance education by integrating face-to-face instruction with digital technologyies. The dataset includeds learner demographics (age, gender, education level, dance experience, and dance type), digital learning effectiveness indicators, cultural immersion and awareness attributes, instructor–learner interaction measures, and self-directed practice and engagement factors captured through Likert-scale responses (Zhou & Sangsawang, 2026).

Source:(https://www.kaggle.com/datasets/ziya07/minority-dance-blended-learning-dataset/data/data)

3.2 Preprocessing using Z-score normalization

Preprocessing is the process of converting raw motion capture Minority Dance Blended Learning data into a format that can be reliably analyzsed to support accurate skill measurement and personalized learning by performing a Z-score normalization to reduce inter-learner variance, provide consistent movement representation, and support robust performance evaluation and meaningful grouping of learners. The normalization is represented byas equation [P1.1]

$$z = \frac{x-\mu}{\sigma} \qquad (1)$$

Here, x_ denotes thean original motion feature value, μ represents the mean of that feature across learners, and σ indicates the standard deviation. Z-score normalization generates standardized motion aspects with lower performer variability, allowing consistent movement comparison and valid learner grouping, facilitating individualized instruction, and effective maintenance of minority dance practices.

3.3 Artificial Gorilla Troop Optimized Conditional Variation Autoencoder (AGTO-CVAE)

The proposed framework utilizes the AGTO-CVAE to enable the precise analysis of students' dance movements and performance assessments. The AGTO-CVAE is a combination of GTO and CVAE[P1.1][Team1.2] learning. The CVAE learns latent representations under contextual input, allowing controlled feature generation and reconstruction. AGTO[P2.1][Team2.2] achieves better stability in convergence, representation strength, and reconstruction accuracy on difficult, high-dimensional movement pattern modelling[P3.1][Team3.2] by optimizsing encoder-decoder parameters and latent distributions.

3.3.1 Conditional Variation Autoencoder (CVAE)

VAEs can also have issues with low control over generated images and poor ability to include contextual information, which limits their use in problems that demand conditional learning, such as like the modelling of dance movements based on culture. The CVAE overcomes these constraints by conditioning both the encoder and decoder on contextual input x which allows learning highly structured and controllable representations. CVAE is used to acquire latent representation of dance moves which are conditioned with contextual and cultural features which enable an accurate model of the performance of students in addition to facilitating the development of skills and deepening cultural knowledge by matching physical performances to movement patterns rooted in heritage information. The conditional likelihood objective is defined as equation (2)

$$logp_{\theta}(y|x) \geq -KL(q_{\phi}(z|x)||p_{\theta}(z|x)) + E_{q\phi}[logp_{\theta}(y|x|z)] = L_{CVAE}(\theta,\phi;x,y) \quad (2)$$

Where L_CVAE (θ,ϕ;x,y) models x as the contextual input, y as the target output, z as the latent variable, q_ϕ (z|x,y)as the approximate posterior, p_θ (z|x)as the conditional prior, the KL divergence term regularizes z, and E_qϕ is the expectation term ensures accurate reconstruction conditioned on xand z. To further emphasize reconstruction fidelity and contextual consistency, the loss can also be expressed as equation (3)

$$L_{rec} = E_{q\phi(z|x|y)}[||y - \hat{y}(x,z)||^{2}] \quad (3)$$

Here, L_{rec} quantifies the discrepancy between the predicted output and the desired target y and the reconstructed output $\hat{y}(x,z)$generated from the latent variable z conditioned on context x. The expectation over $q_{\phi}(z \mid x,y)$ensures that the model learns accurate and context-aware reconstructions across the latent space. The CVAE facilitated contextual latent representations of dance motions while permitting the accurate reconstruction and performance evaluation of dance motions, developing the skill refinement of students, their cultural awareness, and the correspondence of physical practice to heritage-based learning goals.

3.3.2 Artificial Gorilla Troop Optimization (AGTO)

The AGTO algorithm is a nature-inspired, population-based metaheuristic that models the key social behaviors of gorillas, including leadership dynamics, collective group interactions, territorial exploration, and competitive strategies, to guide the optimization process. It uses motion capture features as input and enhances the CVAE by improving the reconstruction accuracy, movement representation, and overall performance assessment. AGTO was used to optimize movement modeling and learner performance evaluation parameters in minority dance education. It aims to maximize the quality of candidate solutions and increase accuracy, flexibility, and conformity to cultural and educational goals.

Exploration Stage

This phase defines the optimization of the AGTO algorithm. Gorillas have silverbacks in charge of making decisions as they venture into new and known territories seeking resources. The AGTO algorithm is used to optimize the parameters for minority dance education with the aim of improving the learning of latent representation, reconstruction accuracy, and performance evaluation by considering culture. Three mechanisms guide exploration, as expressed in equation (4-5).

$$C = F \times \left(1 - \frac{t}{MaxIt}\right) \tag{4}$$

$$L = C \times l \tag{5}$$

Parameter C is designed as $C = F \times (1 - t/MaxIt)$, where $F = \cos(2 \times r_4) + 1$introduces randomness, t represents the extant repetition, and $MaxIt$is is the supreme quantity of reiterations. This allows for larger exploration in the early stages and finer convergence in the later stages. $L = C \times l$ scales this effect using a random factor $l \in [-1,1]$, simulating the leadership influence of the silverback gorilla on guiding search directions.

Exploitation Stage

During the exploitation phase, two main behaviors are used to dictate maximization. The silverback dominates other gorillas in natural groups, and these aggressive behaviors in contests with rivals are simulated as different social strategies in the optimization of the parameters to improve the latent movement representation, reconstruction accuracy, and performance evaluation based on cultural importance. This is represented by equations (6) and (7):

$$GX(t+1) = L \times M \times (X(t) - X_{silverback}) + X(t) \tag{6}$$

$$\delta = 2^L \tag{7}$$

The gorilla's next position $G_X(t+1)$ based on its current position $X(t)$, the optimal silverback position $X_{\text{silverback}}$, and two scaling parameters: L, representing the leadership influence of the silverback, and M, a random factor controlling movement magnitude. The parameter $\delta = 2^L$ adjusts the scaling of the movement based on the leadership factor L, amplifying or reducing the influence of the silverback gorilla on the solution update.

Competition for Adult Females

Competing among other males is one of the behaviors of an adolescent gorilla, which is a mutually influencing solution of the silverback, where the best solution of a silverback shifts towards other solutions and leads current candidates. This engagement leads to better exploration and convergence, latent representation learning, reconstruction, and culturally aware evaluations of minority dance movements. This behavior is simulated using Equation (8-9)

$$Q = 2 \times r_5 - 1 \tag{8}$$
$$A = \beta \times E \tag{9}$$

The parameter $Q = 2 \times r_5 - 1$ generates a random value between -1 and $1 (r_5 \in [0,1])$ to introduce stochasticity in the solution updates. $A = \beta \times E$ scales the influence of competition, where β is a control factor, and E represents the difference between the current and other solution positions. AGTO effectively optimized the model, improving the learning of latent representation, reconstruction accuracy, and stability in convergence. It allowed modeling the movement elements of dances with high accuracy, which facilitated the mastery of the skill and cultural values of the specific item and allowed the correlation of physical activity with the goals of learning according to the heritage. Algorithm 1 shows the AGTO-CVAE process.

Algorithm 1: AGTO–CVAE for Enhancing Minority Dance Education
$Initialize\ dataset\ D, CVAE\ parameters\ (\theta, \phi), and\ AGTO\ population\ X(t), MaxIt$
$Step\ 1: CVAE\ Modeling$
$For\ each\ (x, y)\ in\ D:$
$z = q\phi(z \mid x, y)$
$\hat{y} = p\theta(y \mid x, z)$
$Compute\ L\_CVAE$
$IF\ L\_CVAE\ decreases\ THEN\ update\ \theta, \phi$
$ELSE\ adjust\ learning\ rate$
END
$Step\ 2: AGTO\ Optimization$
$For\ t = 1\ to\ MaxIt:$
$Compute\ C = F \times (1 - t/MaxIt), L = C \times l$
$IF\ exploration\ THEN\ update\ X(t)\ randomly$
$ELSE$
$GX(t+1) = L \times M \times (X(t) - X\_silverback) +$

$\delta = 2\text{^}L$
$IF\ fitness\ improves\ THEN\ accept\ update$
END
$Q = 2 \times r5 - 1;\ A = \beta \times E$
$Adjust\ X(t)\ using\ Q, A$
END
$Return\ \theta *, \phi *$
$Step\ 3: Hybrid\ Evaluation$
$For\ each\ new\ (x\_new, y\_new):$
$z\_new = q\phi(z \mid x\_new, y\_new)$
$\hat{y}\_new = p\theta(y \mid x\_new, z\_new)$
$L\_rec = \lvert\lvert y\_new - \hat{y}\_new \rvert\rvert^2$
$IF\ L\_rec < threshold\ THEN\ performance = accurate$
$ELSE\ fine - tune\ using\ AGTO$ END

The AGTO-CVAE is efficient in capturing and analyzing the movement of students during dance, providing accurate evaluations of performance, facilitating improved mastery of technical skills, and helping to obtain personalized feedback. Its inclusion in the blended learning model enhanced the involvement of learners, cultural awareness, and general proficiency of minority dances.

3.4 K-means clustering

These partitions are used to group learners into different clusters according to the similarity of the characteristics of blended learning and performance. Therefore, we can identify various learning profiles and facilitate individualized instructional plans for teaching minority dances. This is represented by equation (10):

$$J = \sum_{k=1}^{K} \sum_{x_i \epsilon C_k} \lVert x_i - \mu_k \rVert^{2} \tag{10}$$

Here, K denotes the number of clusters, x_i represents a learner's feature vector, C_k is the k-th cluster, and μ_k is its centroid. This algorithm minimizes within-cluster variance by grouping learners with similar engagement, adaptability, and cultural orientation.

K-means clustering provides clear groups of learners that show differences in terms of engagement, technological flexibility, and cultural orientation that create the opportunity to implement individualized instructional plans to address the needs of learners that positively influence the progress of dance skills, cultural awareness, and efficiency of the blended minority dance education model.

3.5 Statistical analysis

Statistical analysis is conducted through EFA to extract the latent learning factors, and hence allow data-driven information to be used to make decisions and enhance the performance of minority dance education.

An EFA was performed on the multidimensional characteristics of the dataset. Latent factors that can be seen as underlying constructs of the blended learning environment were determined by EFA and allowed to reduce dimensionality, identify the most significant effects on learner engagement, and provide specific instructional models to improve the results of minority dance learning. This study was approved by the Faculty of Technical Education, Rajamangala University of Technology, Thanyaburi, Thailand (approval number SU-2025-96418). Dated 14/07/2025.

4 RESULT AND DISCUSSION

This section evaluates the effectiveness of the proposed blended learning framework in supporting minority dance education while also examining its strategic implications for data-driven educational management. Beyond measuring movement recognition accuracy and computational efficiency, the analysis interprets how the analytical outputs generated by the AGTO-CVAE model contribute to educational intelligence and evidence-based decision-making within blended learning environments.

To assess the performance of the proposed system, a series of experiments were conducted using the Minority Dance Blended Learning dataset. The experimental setup, including system configuration, dataset parameters, and evaluation settings, is summarized in Table 1. These experiments were designed not only to evaluate the technical capabilities of the AGTO-CVAE model but also to examine how the resulting analytical insights can support instructional planning, learner monitoring, and institutional decision processes in minority dance education.

Table 1: Experimental configuration for model development and training

Categories	**Specification**
$Processor\ (CPU)$	$Intel\ Core\ i7$
RAM	$32\ GB\ DDR4$
$Graphics\ (GPU)$	$NVIDIA\ RTX\ 4080$
$Operating\ System$	$Windows\ 11\ (64-bit)$
$Programming\ Language$	$Python\ 3.11$
$Storage$	$1\ TB\ NVMe\ SSD$

4.1 Experimental Findings

This subsection presents the experimental analysis through graphical and statistical representations. The findings demonstrate the robustness, accuracy, and operational efficiency of the AGTO-CVAE model under different testing conditions. More importantly, the results also reveal how performance analytics derived from motion capture data can generate actionable intelligence regarding learner behavior, engagement patterns, and skill development.

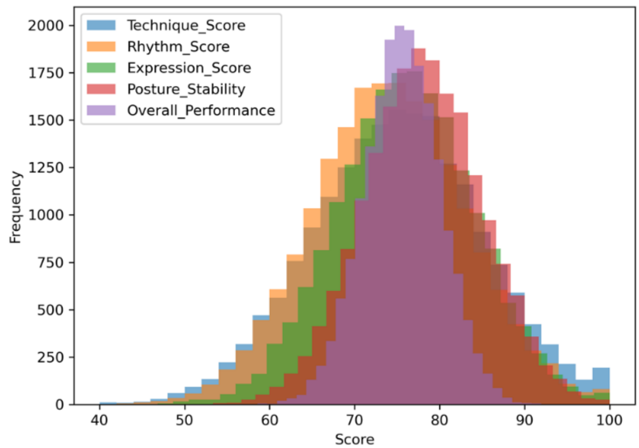

Figure 3: Distribution of dance performance scores across multiple evaluation dimensions

Figure 3 shows the distribution of scores on technique, rhythm, expression, posture stability, and overall performance. The patterns of all the curves are near-normal with a specific range of mid-to-high scores, which means that the learners performed consistently. Such information provides instructors with intelligence about learner progress, enabling targeted instructional adjustments and improved pedagogical planning.

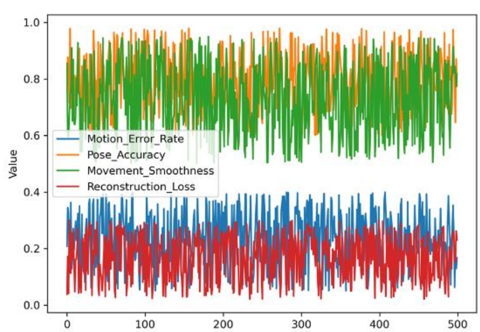

Figure 4: Performance metric trends across motion capture samples in dance education

Figure 4 shows the differences in the rate of motion errors, pose errors, movement smoothness, and reconstruction loss among the samples. The accuracy and smoothness in poses were both consistently high, whereas the motion error rate and reconstruction loss were relatively low. This trend shows a constant movement representation and a consistent performance evaluation in the learning system.

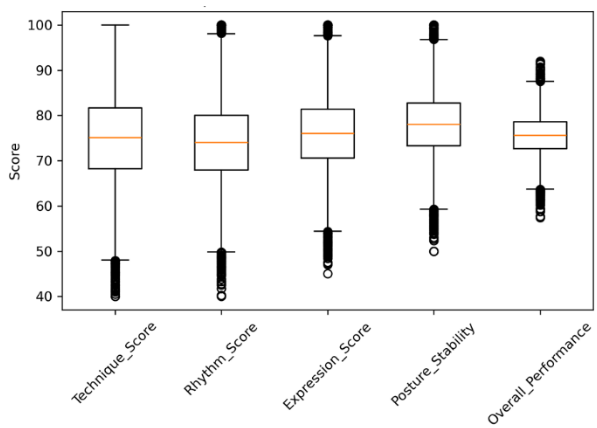

Figure 5: Boxplot comparison of dance performance dimensions in blended learning environment

Figure 5 shows a comparison of the score distribution between technique, rhythm, expression, stability of poses, and general performance. The median scores are consistently high, which indicates equal development of skills. Interquartile ranges were moderate in character, and few outliers implied stable patterns of assessment among learners in the blended learning environment of dance learning.

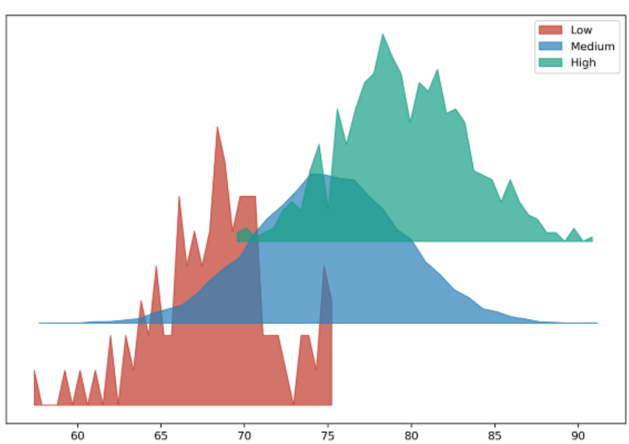

Figure 6: Overall performance distribution across clustered learner proficiency levels

Figure 6 presents the results of the overall performance scores for the low, intermediate, and high groups of learners. The low-level learners fell in the low ranges of the scores, whereas the medium and high groups moved rightward in the ranges.

Categorization of the curves demonstrates a distinct performance division that justifies the grouping of learners in the dance classroom and differentiated teaching plans in blended dance education

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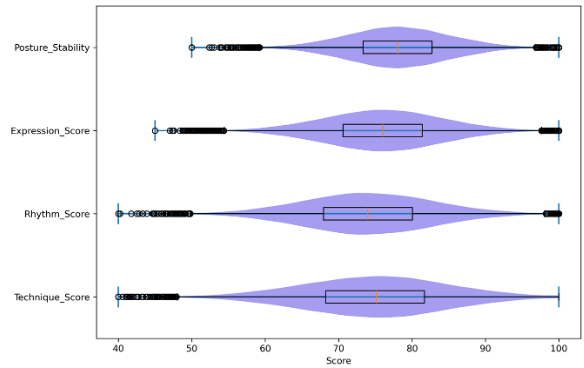

Figure 7: Violin plot distribution of core dance performance dimensions

Figure 7 present scores distributions of technique, rhythm, expression and stability of the posture. The concentration density in more scores range points to the similarity of performance in dimensions. The boxplots embedded within each other display a central tendency and variability, whereas the small extreme values indicate stable assessment patterns using the blended learning framework.

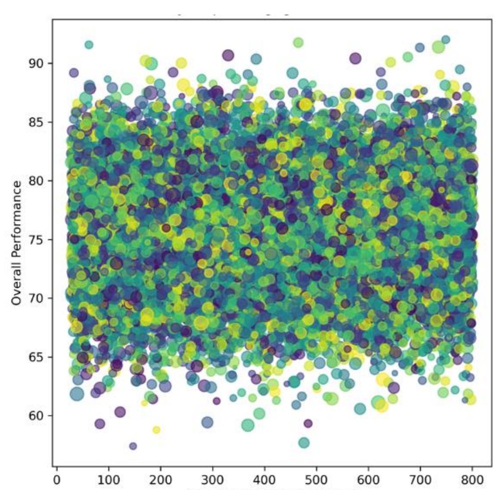

Figure 8: Relationship between video engagement duration and overall dance performance

Figure 8 shows the correlation between video watch time and overall performance. The scores were uniformly spread for different durations of engagement, resulting in stable learning. The high concentration of points indicates that blended learning allows maintaining the consistency of performance regardless of changes in exposure to digital content.

4.2 Comparison phase

The comparison stage compares the proposed AGTO-CVAE with existing methods, such as dual-wing harmonium-multiview metric learning (DWH-MVML) (Zhang & Wang 2024) and three-dimensional convolutional neural networks (3D-ResNet) (Zhen & Keun 2025) based on the effectiveness of recognition through precision, recall, and F1-score, whereas model size, FLOPs, and inference time measure the efficiency of computations and real-time applicability in minority dance education systems.

Precision

Precision measures the percentage of correct movements, as identified by the model, of all movements that the model classifies as correct. It represents the consistency of automated feedback because it reduces the false recognition of movements, which assists valid performance assessment in blended minority dance education. This is represented by equation (11):

$$Precision = \frac{TP}{TP+FP} \tag{11}$$

Where TP denotes correctly recognized dance movements and FP denotes incorrectly recognized movements classified as correct.

Recall

Recall is the ratio of the number of correct movements that learners have recognized to the total number of correct movements that learners have done. It shows how the model is able to capture key movement patterns without exclusion, as it helps to make a complete assessment of performance in blended minority dance education. This is described by equation (12):

$$Recall = \frac{TP}{TP+FN} \tag{12}$$

Where FN denotes correct movements that are not identified by the model.

F1-score

The F1-score is a harmonic mean used to evaluate how accurately and consistently the AGTO-CVAE model recognizes and reconstructs minority dance movements, ensuring a balanced assessment between correctly identified performances and missed or misclassified movements in equation (13).

$$F1 - score = 2 \times \frac{Precision \times \text{Recall}}{Precision + \text{Recall}} \tag{13}$$

A higher F1-score indicates that the AGTO-CVAE model more effectively balances accurate motion recognition (precision) with the comprehensive detection of correct dance patterns (recall), supporting reliable performance evaluation in blended learning.

Model size

This refers to the total memory footprint of the AGTO-CVAE, affecting computational efficiency, faster inference, and practical deployment in blended minority dance learning environments.

Floating Point Operations (FLOPs)

It measures the computational complexity, indicating the processing required for motion analysis and AGTO-CVAE evaluation, directly reflecting the efficiency of dance performance assessment.

Inference time

It represents the duration a model takes to process input and produce predictions, impacting real-time dance performance evaluation, and enhancing learner feedback efficiency.

Table 2: Performance evaluation of dance movement recognition models using classification metrics

Model	Precision	Recall	F1-score
DWH-MVML (Zhang & Wang 2024)	0.9825	0.9802	0.9813
AGTO-CVAE (Proposed)	0.9875	0.9845	0.9859

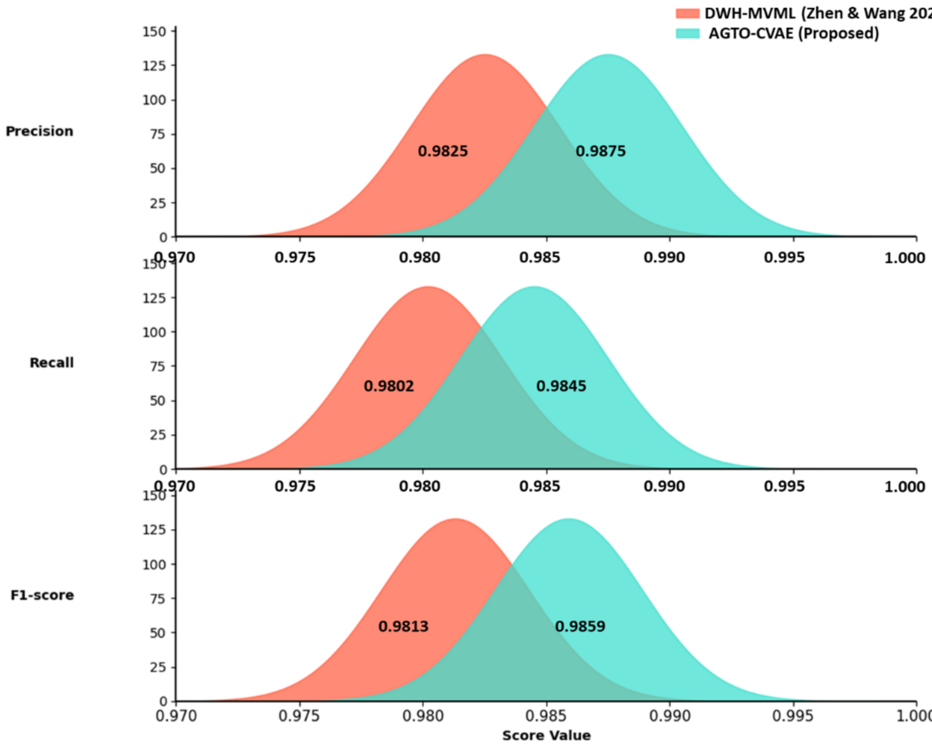

Figure 9: Comparative performance distribution of baseline and AGTO-CVAE models

Table 2 and Figure 9 illustrate the classification performance of DWH-MVML (Zhang & Wang 2024) and AGTO-CVAE. The DWH-MVML model demonstrated strong performance, achieving an F1-score of 0.9813, a recall of 0.9802, and a precision of 0.9825. However, the proposed AGTO-CVAE further enhanced the performance, attaining higher precision (0.9875), recall (0.9845), and F1-score (0.9859), indicating superior accuracy, robustness, and balance in recognition.

Table 3: Comparison of model complexity and runtime efficiency for dance analysis

Model	$\boldsymbol{Model\ size\ (MB)}$	$\boldsymbol{FLOPs\ (G)}$	$\boldsymbol{Inference\ time\ (ms/frame)}$
3D-ResNet (Zhen & Keun 2025)	94.2	42.7	18.2
AGTO-CVAE (Proposed)	60.2	25.6	10.9

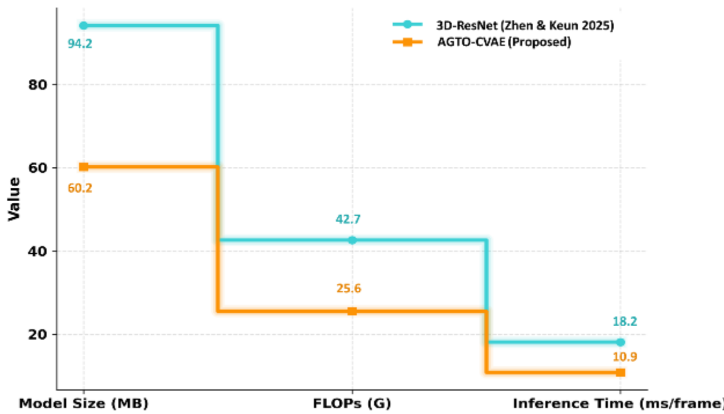

Figure 10: Performance and resource comparison between baseline and proposed dance model

Table 3 and Figure 10 show a comparison of the computational efficiencies of 3D-ResNet (Zhen & Keun 2025) and AGTO-CVAE. 3D-ResNet has a model size of 94.2 MB, 42.7 GFLOPs, and a 18.2 ms per frame inference time. The AGTO-CVAE requires fewer resources with a model size of 60.2 MB, 25.6 GFLOPs, and a frame inference time of 10.9 ms and is more efficient.

Assessment of Exploratory Factor Analysis (EFA)

EFA is used to uncover the latent dimensions of the blended learning environment in minority dance education by examining the relationships among the survey, performance, and digital engagement variables. This EFA utilizes three factors: Factor 1 (engagement) comprises online engagement, face-to-face hours, and instructor interaction. Factor 2 (performance) includes the Technique Score, Rhythm Score, Expression Score, Posture Stability, and Motion Accuracy, representing technical proficiency and expressive execution in dance. Factor 3 (Cultural Dimension) is primarily defined by Cultural_Awareness, indicating learners' understanding and appreciation of the minority dance heritage.

Table 4: Latent factor structure of blended learning attributes in minority dance education

Feature	Factor 1	Factor 2	Factor 3
Online Engagement	0.82	0.10	0.08
FaceToFace_Hours	0.76	0.17	0.14
Instructor Interaction	0.71	0.22	0.15
Technique Score	0.14	0.88	0.05
Rhythm Score	0.11	0.86	0.07
Expression Score	0.08	0.84	0.09
Posture Stability	0.10	0.81	0.11
Motion Accuracy	0.18	0.79	0.06
Cultural_Awareness	0.05	0.06	0.83

Table 4 presents a clear three-factor structure. Factor 1 is driven by engagement-related features, with Online Engagement (0.82), FaceToFace_Hours (0.76), and Instructor Interaction (0.71), which exhibit strong associations, indicating active learner participation. Factor 2 represented performance proficiency, dominated by Technique Score (0.88), Rhythm_Score (0.86), Expression Score (0.84), Posture_Stability (0.81), and Motion Accuracy (0.79). Factor 3 captures the cultural dimension, with Cultural_Awareness loading at 0.83, while the other features show minimal cross-loadings. Values are factor loadings after rotation; bold values indicate strong associations (loading ≥ 0.70).

5 DISCUSSION

The model was effectively developed to help minority dance education and improve skills, cultural awareness, and learners' engagement through the use of AGTO-CVAE. Existing methods have some limitations: DWH-MVML (Zhang & Wang 2024) is based on multi-view feature alignment, which does not allow the promotion of complex motion patterns and subtle dance gestures, whereas 3D-ResNet (Zhen & Keun 2025) is computationally expensive and cannot provide real-time feedback in blended learning. AGTO-CVAE addresses these issues by incorporating optimized conditional latent representations with lower model size and FLOPs, but high precision, allowing AGTO-CVAE to evaluate performance with accuracy, efficiency, and scalability to assess minority dance education. Beyond its technical advantages, the framework contributes to the development of data-driven educational intelligence systems that support the transformation of learning data into actionable insights. Motion capture data, learner engagement metrics, and analytical outputs constitute valuable informational assets that can be systematically analyzed to identify learner behavior patterns, performance dynamics, and learning preferences. Within a data → intelligence → decision-making architecture, these analytical insights function as a form of educational intelligence that can inform instructors and institutional administrators in designing adaptive teaching strategies, optimizing curriculum structures, and improving resource allocation. From the perspective of organizational Competitive Intelligence, the proposed framework demonstrates how data-driven learning systems can support strategic governance in educational institutions.. Such data-driven insights can help institutions improve accessibility to cultural education, monitor learning outcomes, and support sustainable preservation of minority dance traditions through more effective teaching practices. Overall, the integration of artificial intelligence, motion capture analytics, and blended learning environments illustrates the broader potential of intelligent educational systems to support both technical skill development and strategic educational management. In this context, the proposed AGTO-CVAE framework not only advances movement recognition capabilities but also demonstrates how data-driven intelligence systems can strengthen minority dance education, improve institutional decision-making, and support the sustainable transmission of cultural traditions.

6 CONCLUSION

This study proposes a data-driven blended learning framework grounded in the principles of Competitive Intelligence (CI) to support minority dance education. The framework integrates traditional instruction with digital learning technologies, motion capture systems, and the Artificial Gorilla Troop Optimized Conditional Variational Autoencoder (AGTO-CVAE) model to enhance movement analysis accuracy, learner engagement, and the preservation of cultural knowledge in minority dance training. Within the Competitive Intelligence perspective, educational data generated from learning environments function as strategic information resources that can support institutional analysis and decision-making. Data were collected from students participating in minority dance programs using structured questionnaires, performance assessments, and online engagement metrics. In line with the intelligence collection phase, motion capture sequences were preprocessed using Z-score normalization to ensure consistent feature representation across learners. During the intelligence analysis phase, Exploratory Factor Analysis (EFA) was applied to identify key latent dimensions of the learning environment, including digital learning effectiveness, cultural immersion, instructor–learner interaction, and self-directed practice. Additionally, K-means clustering was employed to classify learners according to engagement levels, technological adaptability, and cultural orientation, enabling a deeper analytical understanding of learner behavior patterns. Performance evaluation demonstrates that the proposed AGTO-CVAE model achieves superior results compared with existing approaches. The model obtained an F1-score of 0.9859, recall of 0.9845, and precision of 0.9875, outperforming the DWH-MVML approach. Furthermore, the model exhibited greater computational efficiency than the 3D-ResNet architecture, with a reduced model size (60.2 MB), lower computational cost (25.6 GFLOPs), and faster inference time (10.9 ms per frame). These improvements facilitate more accurate and efficient movement recognition within blended learning environments. From a Competitive Intelligence perspective, the analytical outputs generated by the framework represent the intelligence dissemination stage, where processed insights are translated into actionable knowledge for educators and institutional managers. These insights can support evidence-based instructional strategies, curriculum optimization, and resource allocation decisions, forming part of an intelligence-based decision architecture within educational institutions. In this way, the proposed framework contributes to the development of educational intelligence systems that transform learning data into strategic institutional knowledge.

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Informed Consent Statement: Verbal consent was used because the study involved minimal risk and did not collect sensitive or personally identifiable information. The participants were fully informed about the study purpose, voluntary participation, and confidentiality prior to data collection. In this context, verbal consent was considered ethically appropriate in accordance with the institutional guidelines.

Written consent was waived by the ethics committee, as the study involved minimal risk and did not collect sensitive or personally identifiable information. The committee approved the use of verbal consent, as ethically appropriate for this study.

Data Availability Statement: Dan Zhou; Sangsawang, Thosporn (2026). Blended Learning Model for Enhancing Minority Dance Education Validated through Exploratory Factor and Cluster Analyses. figshare. Dataset. https://doi.org/10.6084/m9.figshare.31557709.v1

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